

# **ESSAYS ON CONSUMER DECISION-MAKING IN INTERACTIVE AND INFORMATION RICH ENVIRONMENTS**

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by

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# **ESSAYS ON CONSUMER DECISION-MAKING IN INTERACTIVE AND INFORMATION RICH ENVIRONMENTS**

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To my family, for their love

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## SUMMARY

This dissertation consists of two central parts. Part one of the dissertation examines the impact of interactive restructuring on decision processes and outcomes. Five experimental studies show that consumers examine less information and engage in more compensatory decision processes when interactive restructuring tools are available. Consumers also increase their use of restructuring tools in cognitively challenging choice environments. The availability of a sorting tool improves objective and subjective decision quality when attributes are positively correlated, or when the number of alternatives in a choice set is large, but not when attributes are negatively correlated or choice sets are small. Greater use of interactive restructuring tools has deleterious effects on decision quality when attributes are negatively correlated. Under time pressure the availability of an interactive restructuring tool improves decision quality, even when attributes are negatively correlated, since time pressure limits tool overuse. Finally, the effects of multiple interactive restructuring tools on decision making vary by the types of tools that marketers make available to consumers.

Part two of the dissertation explores the effects of visual design on consumer preferences and choice. Experiment 1 demonstrates preference reversals when visual separators are between product alternatives versus between product attributes. Experiment 2 shows that when product attributes are negatively correlated, visually separating alternatives improves decision quality but visually separating attributes hurts decision quality. Visual separators do not affect decision quality when attributes are positively correlated. Experiment 3 extends experiment 2 to show that visual separators

enhance decision-making efficiency and can limit the extent to which consumers adapt to contextual changes in choice environments. Finally, experiment 4 shows that, under time pressure, both visual separators between attributes as well as visual separators between alternatives improve decision quality when attributes are negatively correlated.



# **CHAPTER 1**

## **INTRODUCTION**

Part one of the dissertation examines the impact of interactive restructuring on decision processes and outcomes. To help consumers deal with increasing amounts of information, many online marketers offer tools that allow consumers to interactively restructure decision environments, such as the ability to sort on a particular attribute and eliminate particular alternatives. This article proposes that interactive restructuring tools are used by consumers as substitutes for cognitive effort. Five experimental studies show that consumers examine less information and engage in more compensatory decision processes when interactive restructuring tools are available. Consumers also increase their use of restructuring tools in cognitively challenging choice environments. The availability of a sorting tool improves objective and subjective decision quality when attributes are positively correlated, or when the number of alternatives in a choice set is large, but not when attributes are negatively correlated or choice sets are small. Greater use of interactive restructuring tools has deleterious effects on decision quality when attributes are negatively correlated. Under time pressure the availability of an interactive restructuring tool improves decision quality, even when attributes are negatively correlated, since time pressure limits tool overuse. Finally, the effects of multiple interactive restructuring tools on decision making vary by the types of tools that marketers make available to consumers. Results suggest that when attributes are negatively correlated, the ability to sort can lower decision quality when elimination tools are unavailable but increase decision quality when elimination tools are available.

However, when attributes are positively correlated, the ability to sort improves decision quality regardless of the availability of elimination tools.

Part two of the dissertation explores the effects of visual design on consumer preferences and choice. Visual design elements, such as separators between rows or columns of data in a product matrix, are often used by online retailers to enhance the aesthetic appeal or usability of web pages. This article proposes that, although they may enhance usability, seemingly innocuous design changes can systematically influence consumer preferences and choices. Study 2.1 demonstrates preference reversals when visual separators are between product alternatives versus between product attributes. Study 2.2 shows that when product attributes are negatively correlated, visually separating alternatives improves decision quality but visually separating attributes hurts decision quality. Visual separators do not affect decision quality when attributes are positively correlated. Study 2.3 extends study 2.2 to show that visual separators enhance decision-making efficiency and can limit the extent to which consumers adapt to contextual changes in choice environments. Finally, study 2.4 shows that, under time pressure, both visual separators between attributes as well as visual separators between alternatives improve decision quality when attributes are negatively correlated.

## **PART ONE**

### **INTERACTIVE RESTRUCTURING: IMPLICATIONS FOR DECISION PROCESSES AND OUTCOMES**

## **CHAPTER 2**

### **INTRODUCTION TO PART ONE**

To help consumers deal with increasing amounts of information, many marketers offer tools that allow consumers to interactively restructure online environments. For example, on Expedia, consumers can sort hotels by price or by distance to an airport; on Travelocity, they can eliminate those hotels they don't like (see Figure 1). Interactive restructuring tools, such as the ability to sort alternatives on a particular attribute or the ability to eliminate alternatives from view, are different from tools that recommend, and sometimes sort, alternatives based on expected utility (Diehl 2005; Diehl, Kornish, and Lynch 2003; Häubl and Trifts 2000) in that they do not require consumers to indicate the relative importance of different attributes either directly (Diehl, Kornish, and Lynch 2003; Häubl and Trifts 2000), through prior behavior (Ansari, Essegai, and Kohli 2000), through questions about related demographic characteristics or usage intentions, or through conjoint tasks (De Bruyn et al. 2008). This may account for their extensive deployment relative to decision aids that require greater consumer effort (De Bruyn et al. 2008). Nevertheless, the effects of interactive restructuring tools on consumer decision making are not well understood.

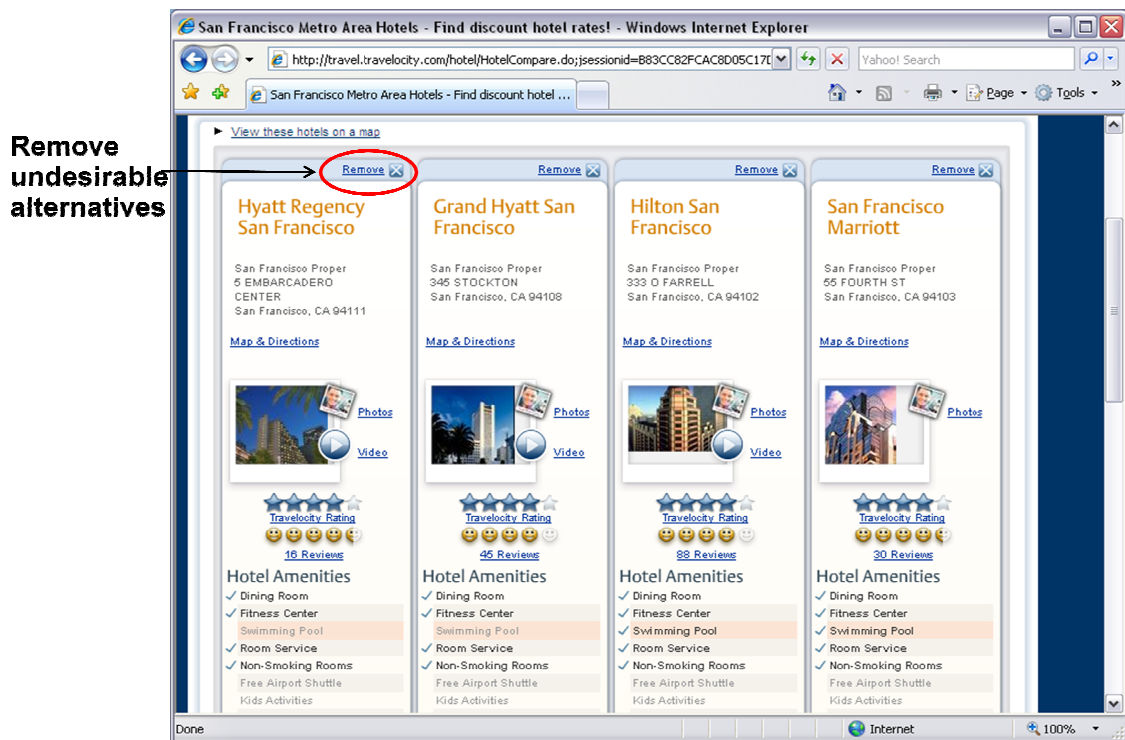
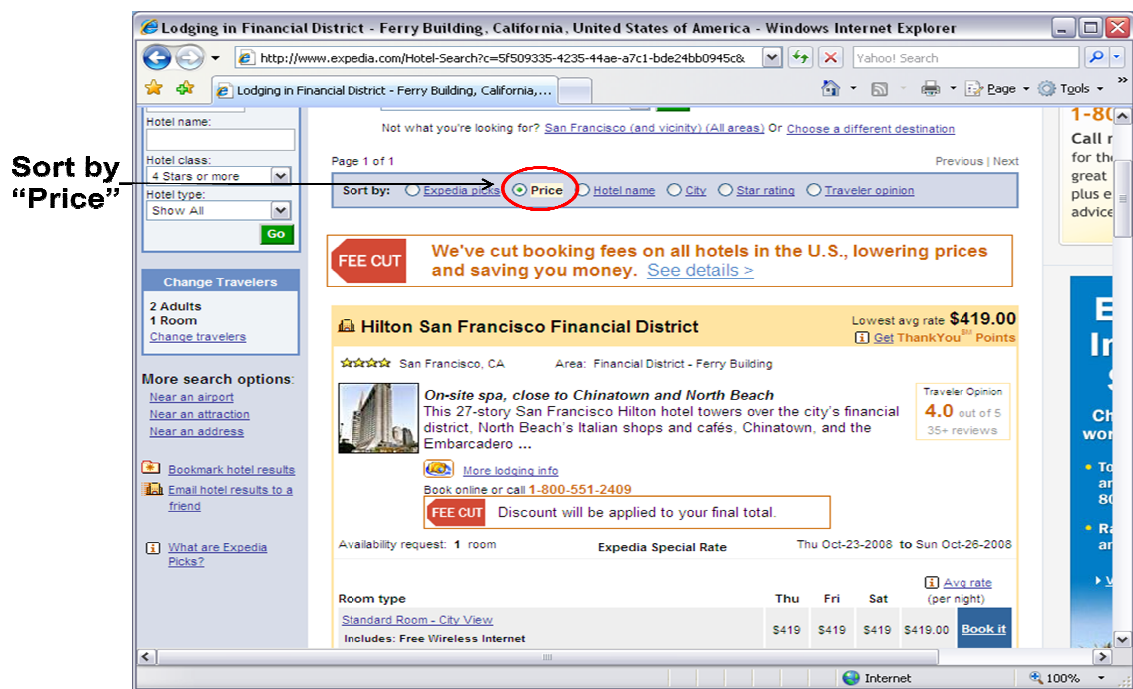


Figure 1

Examples of Interactive Restructuring Tools Used by Online Retailers

In this article, I distinguish between the *availability* of a restructuring tool—which is under the control of the marketer—and the *use* of a restructuring tool—which is under the control of the consumer. I propose that the availability of interactive restructuring tools is likely to focus consumer attention on a subset of alternatives. This should lead them to examine less information but engage in more compensatory evaluations when such tools are available. In addition, I propose that consumers will view interactive restructuring tools as substitutes for cognitive effort and increase their use of these tools in difficult choice environments, such as when attributes are negatively correlated or choice sets are large.<sup>1</sup> By focusing consumer attention on a limited number of alternatives, interactive restructuring tools may improve decision quality—particularly for large choice sets (Alba et al. 1997; Diehl, Kornish, and Lynch 2003; Häubl and Trifts 2000; Hoch and Schkade 1996; Lurie and Mason 2007). However, consumers may inaccurately assess the benefits, and overuse interactive restructuring tools, with negative consequences for decision quality in environments that require more comprehensive evaluation.

This article examines these ideas in a series of experiments in which the ability to sort products on attributes, the ability to eliminate alternatives from view, and the correlation among attributes are manipulated and decision processes and choice quality are measured. Among other results, I find that consumers increase their use of interactive restructuring tools in difficult choice environments, such as when attributes are negatively correlated and choice sets are large. When interactive restructuring tools are available, consumers examine less information and engage in more compensatory decision processes. However, the availability of a sorting tool improves decision quality

when attributes are positively correlated but not when attributes are negatively correlated and, under negative correlation, increased sorting actually leads to performance declines. Under time pressure, however, providing sorting tools improves decision quality under negative as well as positive correlation since time pressure reduces overreliance on these tools. The availability of multiple interactive restructuring tools also has an impact on choice quality depending on characteristics of decision environment. When attribute correlations are negative, the availability of sorting lowers decision quality when elimination tools are not available but increases decision quality when elimination tools are available. However, when attribute correlations are positive, the ability to sort improves decision quality regardless of the availability of elimination tools.

Although prior research has shown that consumers adapt their choice strategies in response to marketer-created information environments (Bettman and Kakkar 1977; Jarvenpaa 1989; Kleinmuntz and Schkade 1993), not much is known about how consumers alter their decision making strategies in the face of marketer-supplied tools that allow them to change the information environment. Also, little is known about when consumers are likely to use such tools. Finally, there is limited research on the conditions in which marketer-provided tools help or do not help consumers make better decisions. By examining how interactive restructuring tools affect decision-making, this article contributes to research on information restructuring (Coupey 1994), adaptive decision-making (Bettman et al. 1993; Payne, Bettman, and Johnson 1988; Payne, Bettman, and Johnson 1993), and consumer-created content (Hoffman and Novak 1996). From a managerial perspective, this research provides insights into how interactive restructuring tools can be deployed in ways that make them helpful to consumers.

## **CHAPTER 3**

### **INTERACTIVE RESTRUCTURING**

Restructuring is a set of processes through which decision makers transform information in order to facilitate decision making (Coupey 1994). Examples include ranking alternatives on particular attribute values, grouping similar options, and separating good from bad options (Coupey 1994). In this article, I define *interactive* restructuring as decision-maker use of marketer-provided tools (such as the ability to sort products by attribute) to transform information environments. This process is interactive because the information environment quickly changes in response to the decision maker's use of a particular tool, and because the decision maker can iteratively transform the information environment and thus engage in a dialogue with the information (Ariely 2000; Lurie and Mason 2007). Interactive restructuring is most likely to occur in electronic environments, where information can be easily customized for individual consumers (Alba et al. 1997; Hoffman and Novak 1996).

#### **3.1 Tool Availability and Decision Processes**

The availability of interactive restructuring tools should change the way in which consumers acquire information and make decisions by allowing consumers to transform information environments. For example, the ability to sort should lead consumers to focus on a subset of alternatives, reducing the amount of information evaluated. This, in turn, should free up cognitive resources allowing consumers to more systematically process a subset of alternatives and lead to increased use of compensatory decision



strategies (Coupey 1994; Kleinmuntz and Schkade 1993; Payne, Bettman, and Johnson 1993).

**H1:** Consumers will a) examine less information and b) engage in more compensatory decision strategies when interactive restructuring tools are available.

### **3.2 Tool Use and Decision Quality**

To the extent that consumers view interactive restructuring tools as substitutes for cognitive effort, they should increase their use of such tools in decision making environments that are more cognitively challenging. Making decisions is more cognitively challenging when attributes are negatively correlated because consumers must make tradeoffs among multiple attributes (Bettman et al. 1993). Consumers are also more likely to be overloaded with information when choice sets are large (Iyengar and Lepper 2000; Lurie 2004).

Importantly, consumers may sometimes over rely on interactive restructuring tools—using them more than the benefits of such tools warrant. For example, when attributes are positively correlated, sorting on different attributes will increase the likelihood the consumer identifies the best alternative—since it will repeatedly be ranked first. However, when attributes are negatively correlated, sorting on different attributes will lead to different alternatives being ranked first and be less effective in reducing the amount of information that needs to be evaluated to make a good decision. Under such conditions, excessive reliance on a restructuring tool may actually reduce decision quality.

**H2:** Consumers will increase their use of interactive restructuring tools in cognitively challenging choice environments.

**H3:** The extent to which the availability of an interactive restructuring tool improves decision quality depends on the extent to which the tool reduces the amount of information that needs to be processed to make a good decision.

Study 1.1 tests these hypotheses by examining how consumer use of restructuring tools is affected by choice context and how restructuring tools impact decision quality in different choice contexts. Study 1.2 extends study 1.1 and tests the hypothesis that how the availability of restructuring tools affects decision processes.

## **CHAPTER 4**

### **STUDY 1.1**

#### **4.1 Method and Procedure**

Participants (116 undergraduate students) participated for course credit in a study in which they were asked to imagine they were buying a calculator for a friend's birthday and had decided to order the calculator from an online retailer of consumer electronics, Electronics USA. They were told that all of the calculators cost \$29.95, which was within their budget.

Next, participants were told that a recent article in Consumer Reports suggested that there were several attributes they should consider when buying a calculator: versatility, ease of use, battery life, warranty, weight, and memory. To help participants in their decisions, their friend had indicated the importance of these attributes on a scale from 1 to 100, where 100 was the most important and the sum of the attributes was 100. Participants were told to use these weights in their decisions. This agent task provides a normative sense of choice goodness and avoids potential measurement errors associated with using participants' own preferences to determine the best choice (Keller and Staelin 1989; Meyer and Johnson 1989; Payne, Bettman, and Johnson 1993).

Following previous research (Bettman et al. 1993), attribute values were randomly generated from a multivariate normal distribution that ranged from 1 to 1000--with 1 as the worst and 1000 as the best. Attribute weights were randomly chosen from a uniform distribution and rescaled to sum to 100. Each choice set was presented as an 18 x 6 matrix with alternatives in rows and attributes in columns. Participants were told that the first row contained the friend's attribute weights for the six attributes. The next 18

rows contained the attribute values for each alternative. At the bottom of the screen, participants could select their preferred alternative among the 18 available alternatives. At the top of the screen, an indicator showed the decision number. Participants were instructed to take as much time as they wished to view information about weights and attribute values and make a decision. Participants made a practice decision followed by 10 actual decisions. For each decision, participants were reminded that the first row contained the friend's attribute weights and they needed to use those weights to make the best choice for their friend. The experimental session took roughly 20 minutes.

## **4.2 Experimental Variables**

### **4.2.1 Availability of an Interactive Restructuring Tool**

Participants were randomly assigned to make decisions either using an interface that offered a sorting tool or an interface that did not offer a sorting tool. To sort, participants in the sorting-present condition just needed to select an attribute and then click the “sort” button. Alternatives were then sorted in descending order (best at the top) by that attribute. Other aspects of the interface were identical across conditions.

### **4.2.2 Attribute Correlation**

Following previous research, to provide a strong test of adaptivity (Bettman et al. 1993), attribute correlation was manipulated within subjects. Choice sets were randomly generated from a multivariate normal distribution to create five with an average pairwise attribute correlation of .60 and another five with an average pairwise attribute correlation of -.20.<sup>2</sup> The order of choice sets was random but the same for all participants. In summary, in Study 1.1, the availability of an interactive restructuring tool was

manipulated between subjects and attribute correlation and trial were manipulated within subjects.

### **4.3 Dependent Variables**

#### **4.3.1 Use of Interactive Restructuring Tools**

Tool use was measured as a count of the number of times that participants sorted in each choice set. This variable was only calculated for participants assigned to the condition in which sorting was available.

#### **4.3.2 Objective Decision Quality**

The objective quality of decisions was assessed through relative choice utility and the probability that the chosen alternative was the best or one of the best three in the choice set. Relative choice utility was measured as the weighted additive utility of the chosen alternative compared with those of the best and worst choice in each choice set (Payne, Bettman, and Johnson 1988). This measure is bounded by 1 if the best choice is selected and 0 if the worse choice is selected.

### **4.4 Results**

Means for the dependent measures are presented in Table 1. The mean quality of participants' choices was fairly high ( $M = .85$ ). On average, participants spent 30 seconds on each decision. In addition, participants for whom sorting was available sorted an average of 2.6 times per choice set. Throughout the paper, I use repeated-measures analyses to account for within-subjects effects. Across the five studies, I did not find consistent effects of trial on the dependent measures.

**Table 1**  
**Study 1.1: Interactive Restructuring Tools and Decision Quality**

Dependent measure	No sorting tool		Sorting tool available	
	Negative correlation	Positive correlation	Negative correlation	Positive correlation
Sorts	--	--	2.76	1.88
Objective decision quality	.82	.85	.81	.90
Probability of choosing the best alternative <sup>a</sup>	.25 (72/285)	.34 (96/285)	.24 (72/295)	.43 (128/295)
Probability of choosing one of three best alternatives	.59 (168/285)	.69 (196/285)	.65 (192/295)	.84 (249/295)

<sup>a</sup> The proportion of participants that chose the best or one of the best three alternatives in each condition are shown. Actual frequencies are shown in parentheses.

#### **4.4.1 Use of Interactive Restructuring Tools**

In support of Hypothesis 2, results show that participants for whom sorting was available sorted more in negatively correlated choice environments than in positively correlated ones ( 3.02 versus 2.24;  $F(1, 58) = 10.89, p < .01$ ). In other words, participants were adaptive in their use of interactive restructuring tools.

#### **4.4.2 Objective Decision Quality**

Because the range of expected values for alternatives in negatively correlated sets is smaller than those for positively correlated sets (Bettman et al. 1993), I conducted a Generalized Estimation Equations (GEE) repeated measures regression on relative accuracy with correlation the range of expected values in each choice set as a trial-specific covariate. In support of Hypothesis 3, that the extent to which the availability of an interactive restructuring tool improves decision quality depends on the extent to which

the tool reduces the amount of information that needs to be processed to make a good decision, there was a significant interaction between interattribute correlation and the availability of a sorting tool (Wald  $\chi^2(1, N = 1160) = 4.16, p < .05$ ). Pairwise comparisons show that the sorting tool helped when attributes were positively correlated (.90 vs. .85;  $t(1160) = 1.82, p < .04$ , one-tailed) but not when they were negatively correlated (.81 vs. .82;  $t < 1$ ). GEE results show that decision quality was higher when attribute correlations were positive than negative (Wald  $\chi^2(1, N = 1160) = 19.46, p < .0001$ ) but revealed no significant main effect of the availability of a sorting tool. Similar results were found in a repeated-measures GLM analysis that did not control for the range of expected values.

Results for the choice probability measures were similar. GEE repeated logistic regression analyses revealed significant interactions between the availability of sorting tools and interattribute correlations in terms of the probability of choosing the best alternative (Wald  $\chi^2(1, N = 1160) = 4.70, p < .05$ ) and in terms of the probability of choosing one of the top three alternatives (Wald  $\chi^2(1, N = 1160) = 5.92, p < .05$ ). Pairwise comparisons show that when attributes were positively correlated, the availability of sorting tools increased the probability of choosing the best alternative (proportions = .43 vs. .34,  $z = 2.63, p < .05$ ) and one of the top three alternatives (proportions = .84 vs. .69,  $z = 3.33, p < .01$ ). However, when attributes were negatively correlated no such effects were found ( $z$ 's  $< 1$ ). Results also show that the probability of choosing the best alternative (Wald  $\chi^2(1, N = 1160) = 36.33, p < .0001$ ), or one of the top three alternatives (Wald  $\chi^2(1, N = 710) = 32.41, p < .0001$ ), was higher when attribute correlations were positive than when they were negative. Finally, the availability of sorting tools increased the probability of choosing the best alternative (Wald  $\chi^2(1, N =$

1160) = 1.89,  $p < .09$ , one-tailed) or one of the top three alternatives (Wald  $\chi^2(1, N = 1160) = 6.67, p < .05$ ).

#### 4.5 Additional Analyses

To better understand the decision quality results, I assessed how the *use* of an interactive restructuring tool affects decision quality. GEE repeated measures regression, with range of expected values as a covariate, shows an interaction between attribute correlation and number of sorts on relative accuracy (Wald  $\chi^2(13, N = 590) = 5644.83, p < .0001$ ). Linear trend analyses show that an increase in the number of sorts improved relative accuracy when attributes were positively correlated ( $\beta = .19$ , Wald  $\chi^2(1, N = 295) = 20.60, p < .0001$ ) but decreased accuracy when attributes were negatively correlated ( $\beta = -.08$ , Wald  $\chi^2(1, N = 295) = 2.82, p < .05$ , one-tailed). In other words, increased use of the restructuring tool has positive effects under positive correlation but adverse effects under negative correlation.

#### 4.6 Discussion

Results from Study 1.1 provide support for the prediction that consumers are more likely to use interactive restructuring tools in cognitive challenging choice environments—such as those in which attributes are negatively correlated. Results also show that the availability of a sorting tool helps consumers make better decisions when attributes are positively correlated. Interestingly, however, the availability of sorting does not help when attributes are negatively correlated because unlike under positive correlation, increased use of sorting tools has adverse effects under negative correlation.



By changing the way in which information is presented, interactive restructuring tools may change the nature of the decision task and therefore the way in which decisions are made. Study 1.2 uses a process tracing system to test the effect of interactive restructuring tools on decision processes.

## **CHAPTER 5**

### **STUDY 1.2**

#### **5.1 Stimuli and Procedure**

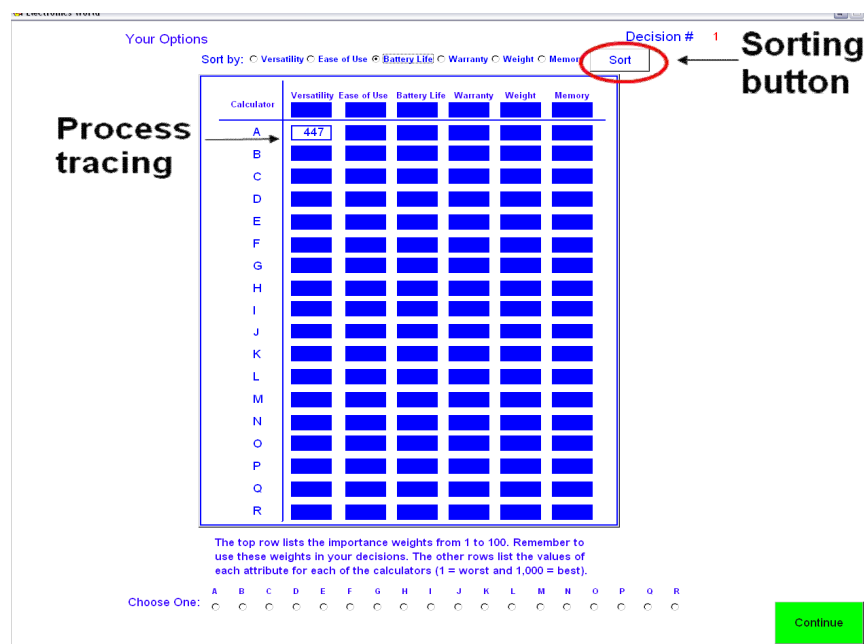
Participants (71 undergraduate students) participated in a study for course credit study in which they were asked to imagine they were buying a calculator for a friend's birthday and had decided to order the calculator from an online retailer of consumer electronics, Electronics USA. They were told that all of the calculators cost \$29.95, which was within their budget.

#### **5.2 Information Acquisition System**

To measure decision processes, Study 1.2 used an information acquisition system similar to Mouselab (Bettman, Johnson, and Payne 1990; Payne, Bettman, and Johnson 1988) developed specifically for this study. Information about attribute weights and values was hidden behind opaque boxes. Information was available for only one box at a time. Moving the mouse cursor over a box revealed its contents, and information remained visible until the cursor was moved out of the box (see Figure 2). Participants could open as many boxes as many times as they wished. The boxes opened, the order and time they were opened were recorded.

Process tracing methods such as Mouselab (Payne, Bettman, and Johnson 1988) may be used to assess information acquisition and decision strategies. For example, in Mouselab, the amount of unique information acquired can be assessed by counting the number of unique boxes opened (Lurie 2004). The degree to which consumers use compensatory decision making processes, in which tradeoffs are made across multiple

attributes (Payne, Bettman, and Johnson 1988), versus non-compensatory decision rules, in which comparisons are made on a single piece of information (or aspect, Tversky 1972), can be assessed through the variance in time spent on each attribute, the proportion of time spent on the most important attribute (Creyer, Bettman, and Payne 1990; Payne, Bettman, and Johnson 1988), and the extent to which decision makers process information by-attribute or by-alternative. Lower variance in time per attribute, a lower proportion of time on the most important attribute, and processing by alternative, are associated with more compensatory decision making processes (Payne, Bettman, and Johnson 1988). Prior research has shown that patterns of information acquisitions in Mouselab are similar to those from eyetracking studies (Lohse and Johnson 1996).



**Figure 2**

### **Study 1.2 process tracing interface**

### **5.3 Experimental Variables**

In Study 1.2, attribute correlation and the availability of an interactive restructuring tool were manipulated as in Study 1.1.

### **5.4 Dependent Variables**

Tool usage and objective decision quality were measured as in Study 1.1. In addition, information acquisition and decision strategies were collected to examine the effect of restructuring tools on decision processes.

#### **5.4.1 Information Acquisition and Decision Strategies**

The amount of unique information acquired was calculated as the proportion of boxes containing attribute information that were opened at least one time per decision (Lurie 2004). The extent to which participants engaged in compensatory decision making was measured through the percentage of time spent acquiring information about the most important attribute, the variance in acquisition time per attribute, and the acquisition pattern. Moving the mouse from one attribute to another for the same alternative was coded as an alternative-based transition. Moving the mouse from one alternative to another for the same attribute was coded as an attribute-based transition (Payne, Bettman, and Johnson 1988). An acquisition pattern index was calculated by taking the number of alternative-based transitions minus the number of attribute-based transitions and then dividing by the sum of alternative- and attribute-based transitions (Bettman et al. 1993). This index ranges from -1 (indicating only attribute-based processing) to +1 (indicating only alternative-based processing). Among the 71 participants in Study 1, four did not

acquire enough information on at least one of the 10 choice sets to calculate an acquisition pattern.

## 5.5 Results

Means for the dependent measures are presented in Table 2. Log transforms were used to correct for skewness in time-based measures (Bettman et al. 1993). Reported values are exponential transforms of these logs.

**Table 2**

**Study 1.2: Interactive Restructuring Tools, Decision Quality, and Decision Processes**

Dependent measure	No sorting tool		Sorting tool available	
	Negative correlation	Positive correlation	Negative correlation	Positive correlation
Sorts	--	--	2.76	1.88
Objective decision quality	.84	.87	.84	.96
Probability of choosing the best alternative	.40 (75/190)	.38 (73/190)	.39 (64/165)	.53 (88/165)
Probability of choosing one of three best alternatives	.66 (126/190)	.75 (143/190)	.65 (107/165)	.92 (151/165)
Unique cells examined (%)	23.72	20.29	12.52	8.54
Proportion of time on the most important attribute	.34	.36	.28	.25
Variance in proportion of time per attribute	6.33	4.02	2.45	.68
Acquisition pattern	.03	.03	.19	.20

### 5.5.1 Information Acquisition and Decision Strategies

In support of Hypothesis 1a, that the availability of an interactive restructuring tool will reduce the amount of information examined, repeated-measures GLM analysis shows that the availability of sorting tools led to a decrease in the percentage of unique cells examined (10.34% vs. 21.94%;  $F(1, 69) = 35.07, p < .0001$ ). Results also support Hypothesis 1b, that the availability of an interactive restructuring tool will increase the use of compensatory decision strategies. In particular, the ability to sort on an attribute reduced the proportion of time spent on the most important attribute (.26 vs. .35;  $F(1, 69) = 10.52, p < .01$ ), the variance in time spent per attribute (1.29 vs. 5.05;  $F(1, 69) = 30.32, p < .0001$ ), and led to greater alternative-based processing (.20 vs. .03;  $F(1, 65) = 2.83, p < .05$ , one-tailed). In addition, the percentage of unique cells examined (17.24% vs. 13.16%;  $F(1, 69) = 35.86, p < .0001$ ) and the variance in time spent per attribute (3.94 vs. 1.65;  $F(1, 69) = 91.88, p < .0001$ ) were higher when attributes were negatively versus positively correlated. No main effects of attribute correlation on the proportion of time spent on the most important attribute or acquisition pattern were found ( $F < 1$ ).

In support of the idea that the effectiveness of interactive restructuring tools depends on choice context, there was a significant interaction between attribute correlations and the availability of a sorting tool on the percentage of unique cells examined ( $F(1, 69) = 6.33, p < .05$ ). The availability of a sorting tool reduced the percentage of unique cells examined to a greater extent when attributes were positively correlated (8.53% vs. 20.29%;  $F(1, 69) = 13.23, p < .0001$ ) than when attributes were negatively correlated (12.53% vs. 23.72%;  $F(1, 69) = 19.37, p < .0001$ ). The effects of a sorting tool on the degree of compensatory decision making are less clearly affected by

interattribute correlations. There was a significant interaction between attribute correlations and the availability of a sorting tool on variance in acquisition time per attribute ( $F(1, 69) = 20.92, p < .0001$ ). The availability of a sorting tool reduced variance in time spent per attribute to a greater extent when attributes were negatively correlated (2.45 vs. 6.33;  $F(1, 69) = 13.68, p < .0001$ ) than when they were positively correlated (0.68 vs. 4.02;  $F(1, 69) = 43.13, p < .0001$ ). However, the interaction between attribute correlation and the availability of a sorting tool ( $F(1, 69) = 4.73, p < .05$ ) on time spent on the most important attribute shows the opposite effect. The availability of a sorting tool reduced the proportion of time spent on the most important attribute to a greater extent when attributes were positively correlated (.25 vs. .36;  $F(1, 69) = 14.56, p < .0001$ ) than when attributes were negatively correlated (.28 vs. .34;  $F(1, 69) = 4.81, p < .05$ ). The interaction between the availability of a sorting tool and attribute correlation did not have a significant effect on acquisition patterns ( $F < 1$ ).

### **5.5.2 Use of Interactive Restructuring Tools**

In support of Hypothesis 2, that consumers are more likely to use tools in cognitively challenging choice environments, GLM results show that participants in the sorting condition sorted negatively correlated choice sets more times than positively correlated ones (2.76 vs. 1.88;  $F(1, 32) = 12.14, p < .01$ ).

### **5.5.3 Objective Decision Quality**

As in Study 1, in support of Hypothesis 3, there was a significant interaction between interattribute correlation and the availability of a sorting tool (Wald  $\chi^2(1, N = 710) = 6.78, p < .01$ ). Pairwise comparisons show that the sorting tool helped when attributes were positively correlated (.96 vs. .87;  $t(710) = 2.43, p < .05$ ) but not when they

were negatively correlated (.84 vs. .84;  $t < 1$ ). GEE results show that decision quality was higher when attribute correlations were positive than negative (Wald  $\chi^2(1, N = 710) = 20.12, p < .0001$ ) but revealed no significant main effect of the availability of a sorting tool. Similar results were found in a repeated-measures GLM analysis that did not control for the range of expected values.

Results for the choice probability measures were similar. GEE repeated logistic regression analyses revealed significant interactions between the availability of sorting tools and interattribute correlations in terms of the probability of choosing the best alternative (Wald  $\chi^2(1, N = 710) = 6.12, p < .05$ ) and in terms of the probability of choosing one of the top three alternatives (Wald  $\chi^2(1, N = 710) = 14.14, p < .0001$ ). Pairwise comparisons show that when attributes were positively correlated, the availability of sorting tools increased the probability of choosing the best alternative (proportions = .53 vs. .38,  $z = 3.02, p < .01$ ) and one of the top three alternatives (proportions = .92 vs. .75,  $z = 2.56, p < .05$ ). However, when attributes were negatively correlated no such effects were found ( $z$ 's  $< 1$ ). Results also show that the probability of choosing the best alternative (Wald  $\chi^2(1, N = 710) = 4.53, p < .05$ ), or one of the top three alternatives (Wald  $\chi^2(1, N = 710) = 38.71, p < .0001$ ), was higher when attribute correlations were positive than when they were negative. Finally, the availability of sorting tools marginally increased the probability of choosing the best alternative (Wald  $\chi^2(1, N = 710) = 3.63, p < .10$ ) or one of the top three alternatives (Wald  $\chi^2(1, N = 710) = 5.42, p < .10$ ).



## 5.6 Additional Analyses

To further better understand the decision quality results, as in Study 1.1, I assessed how the *use* of an interactive restructuring tool affects decision quality. GEE repeated measures regression, with range of expected values as a covariate, shows an interaction between attribute correlation and number of sorts on relative accuracy (Wald  $\chi^2(9, N = 330) = 6259.58, p < .0001$ ). Linear trend analyses show that an increase in the number of sorts improved relative accuracy when attributes were positively correlated ( $\beta = .05$ , Wald  $\chi^2(1, N = 165) = 4.11, p < .05$ ) but decreased accuracy when attributes were negatively correlated ( $\beta = -.29$ , Wald  $\chi^2(1, N = 165) = 67.91, p < .0001$ ). Results also show that increased sorts reduced relative accuracy overall ( $\beta = -.36$ , Wald  $\chi^2(13, N = 330) = 26262.85, p < .0001$ ) suggesting that overreliance on interactive restructuring tools has detrimental effects on choice quality.

## **CHAPTER 6**

### **STUDY 1.3**

Study 1.2 provides additional support for the idea that interactive restructuring tools are more likely to be used in cognitively challenging environments but improvements in decision quality depend on the extent to which a given tool reduces the amount of information that consumers need to process to make good decisions. In particular, tool use is higher when attributes are negatively correlated; yet the availability of sorting leads to improvements in decision quality only when attributes are positively correlated. In fact, increased use of sorting decreases decision quality when attributes are negatively correlated. Together, these results suggest that consumers may sometimes be maladaptive in their use of interactive restructuring tools.

Another example of a cognitively challenging environment is one in which there are many alternatives to choose from. Because greater information processing is required to make good decisions in such environments, consumers are more likely to be overloaded with information, leading to declines in decision quality and choice deferral (Iyengar and Lepper 2000; Lurie 2004). This suggests that consumers should increase their use of interactive restructuring tools, and that the availability of an interactive restructuring tool will improve decision quality to a greater extent, when making decisions from larger choice sets. Study 1.3 tests these ideas by examining how the effects of interactive restructuring tools depend on choice set size in addition to interattribute correlation.

Although Studies 1.1 and 1.2 suggest that consumers may be unable to accurately assess the value of interactive restructuring tools, in that they sort more when attributes are negatively correlated but do not realize improvements in objective decision quality, it may be that the availability of an interactive restructuring tool leads to improvements in *subjective* decision quality. That is, perhaps consumers feel better about their decisions when they have access to such tools. Different effects of decision aids on objective and subjective decision quality have been found in other contexts (Lilien, Van Bruggen and Starke 2004) so it is possible that interactive restructuring tools affect these two dimensions of decision quality in different ways.

However, there are reasons to believe that subjective evaluations will reflect objective ones. In particular, consumers are likely to be sensitive to the extent and rate at which a decision aid improves the choice environment (Diehl and Zauberan 2005). In other words, as with objective choice quality, the greater the extent to which an interactive restructuring tool reduces the amount of information that consumers need to process, the more satisfied consumers will be with their decisions. For example, if sorting tools are more efficient at bringing the best alternatives to the top when attributes are positively correlated, and have more dramatic effects in reducing information processing requirements when there are many alternatives, subjective choice quality should be improved to a greater extent in these environments. Accordingly, Study 1.3 measures subjective as well as objective choice quality.

## **6.1 Stimuli and Procedure**

In addition to manipulating interattribute correlation within subjects, and the availability of a sorting tool between subjects, Study 1.3 varied the number of alternatives between subjects at two levels (6 vs. 18; see Figure 3). As in Studies 1.1 and 1.2, participants made one practice and 10 actual decisions from randomly-generated choice sets defined by six attributes and information was covered by opaque boxes to allow process tracing. Dependent measures in Study 1.3 were identical to those in Study 1.2, but probabilities of choosing the best or one of the best three alternatives were corrected for chance (Malhotra 1982). Following Diehl and Zauberger (2005), subjective decision quality was measured using four 7-point scales (Cronbach's  $\alpha = .83$ ): "How satisfied are you with the calculator you chose for your friend?," "How confident are you that you made the right choice?," "Considering all calculators you looked at, how satisfied were you with this set of calculators, keeping in mind the preferences of your friend?," and "How satisfied were you with the overall calculator search experience?" with higher numbers indicating greater satisfaction. Seventy-four undergraduate students participated for course credit.

Decision # 1

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the calculators (1 = worst and 1,000 = best).

Sort by: ☐ Versatility ☐ Ease of Use ☐ Battery Life ☐ Warranty ☐ Weight ☐ Memory

Sort

Calculator	Versatility	Ease of Use	Battery Life	Warranty	Weight	Memory
A						
B						
C						
D						
E						
F						

Please Choose One Calculator:

A B C D E F

Question 1: How satisfied are you with the calculator you chose for your friend?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very Satisfied

Question 2: How confident are you that you made the right choice?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very Confident

Question 3: How hard was it to make this decision?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not hard Very hard

Question 4: If you had to search again for a calculator for this person in the future, what is the likelihood that you would use this site again to look for another calculator?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all likely Very likely

Question 5: Considering all calculators you looked at, how satisfied were you with this set of calculators, keeping in mind the preferences of your friend?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very satisfied

Question 6: How satisfied were you with the overall calculator search experience?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very satisfied

Continue

Decision # 1

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the calculators (1 = worst and 1,000 = best).

Your Options

Sort by: ☐ Versatility ☐ Ease of Use ☐ Battery Life ☐ Warranty ☐ Weight ☐ Memory

Sort

Calculator	Versatility	Ease of Use	Battery Life	Warranty	Weight	Memory
A						
B						
C						
D						
E						
F						
G						
H						
I						
J						
K						
L						
M						
N						
O						
P						
Q						
R						

Please Choose One Calculator:

A B C D E F G H I J K L M N O P Q R

Question 1: How satisfied are you with the calculator you chose for your friend?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very Satisfied

Question 2: How confident are you that you made the right choice?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very Confident

Question 3: How hard was it to make this decision?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not hard Very hard

Question 4: If you had to search again for a calculator for this person in the future, what is the likelihood that you would use this site again to look for another calculator?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all likely Very likely

Question 5: Considering all calculators you looked at, how satisfied were you with this set of calculators, keeping in mind the preferences of your friend?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very satisfied

Question 6: How satisfied were you with the overall calculator search experience?

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7

Not at all Very satisfied

Continue

Figure 3

## Study 1.3 Interface

## 6.2 Results

### 6.2.1 Information Acquisition and Decision Strategies

Further supporting Hypothesis 1a, the availability of a sorting tool led to a decrease in the percentage of unique cells examined (14.59% vs. 29.87%;  $F(1, 70) = 34.09, p < .0001$ ). As in Study 1.2, there was a significant interaction between attribute correlations and the availability of a sorting tool on the percentage of unique cells examined ( $F(1, 70) = 11.91, p < .01$ ) such that the availability of a sorting tool reduced

the percentage of unique cells examined to a greater extent when attributes were positively correlated (11.92% vs. 27.30%;  $F(1, 70) = 43.74, p < .0001$ ) than when attributes were negatively correlated (17.84% vs. 32.67%;  $F(1, 70) = 22.15, p < .0001$ ). Means for the dependent measures are presented in Table 3.

Of the 74 participants, four did not acquire enough information in at least one of the 10 choice sets to calculate an acquisition pattern. Providing additional support for Hypothesis 1b, that consumers engage in more compensatory decision strategies when a sorting tool is present, the availability of a sorting tool reduced the proportion of time spent on the most important attribute (.37 vs. .47;  $F(1, 70) = 6.21, p < .05$ ), the variance in time spent per attribute (1.10 vs. 4.50;  $F(1, 70) = 358.10, p < .0001$ ), and led to greater alternative-based processing (.19 vs. -.07;  $F(1, 66) = 6.38, p < .05$ ). As in Study 1.2, attribute correlation had mixed effects on how the availability of a sorting tool affected the use of compensatory decision strategies. There was a significant interaction between attribute correlations and the availability of sorting tools on variance in acquisition time per attribute ( $F(1, 70) = 5.57, p < .05$ ). Planned contrasts show that the availability of sorting tools reduced variance in time spent per attribute to a greater extent when attributes were negatively correlated (1.63 vs. 5.31;  $F(1, 70) = 15.53, p < .0001$ ) than when they were positively correlated (.74 vs. 3.81;  $F(1, 70) = 34.66, p < .0001$ ). However, the interactions between attribute correlation and the availability of sorting tools on time spent on the most important attribute or on the acquisition pattern were not significant. Other effects on decision strategies were also not significant.

**Table 3**

**Study 1.3: Choice Set Size and Interattribute Correlation**

Dependent measure	No sorting tool				Sorting tool available			
	6 alternatives		18 alternatives		6 alternatives		18 alternatives	
	- <sup>a</sup>	+ <sup>a</sup>	-	+	-	+	-	+
Sorts	--	--	--	--	1.67	1.46	4.11	3.23
Objective decision quality	.95	.97	.87	.86	.89	.97	.91	.97
Probability of choosing the best alternative <sup>b</sup>	.78 (57/70)	.67 (51/70)	.23 (29/105)	.33 (39/105)	.55 (59/95)	.63 (66/95)	.28 (32/100)	.49 (52/100)
Probability of choosing one of three best alternatives	.94 (68/70)	1.00 (70/70)	.60 (70/105)	.67 (76/105)	.81 (86/95)	1.00 (95/95)	.74 (78/100)	.90 (92/100)
Subjective decision quality	4.39	5.18	4.58	5.04	4.61	5.33	4.22	5.20
Unique cells examined (%)	47.44	39.68	22.50	18.79	28.69	19.22	11.09	7.41
Proportion of time on the most important attribute	.44	.42	.51	.50	.40	.39	.35	.34
Variance in proportion of time per attribute	3.22	1.95	8.73	7.44	1.29	.69	2.07	.79
Acquisition pattern	-.092	-.055	-.055	-.085	.028	.101	.299	.345

<sup>a</sup> “-”: Negative correlation; “+”: Positive correlation.

<sup>b</sup> The proportion of participants that chose the best or one of the best three alternatives in each condition corrected for chance following Malhotra (1982) are shown. Actual frequencies are shown in parentheses.

### 6.2.2 Use of Interactive Restructuring Tools

In further support of Hypothesis 2, that the use of interactive restructuring tools will be higher in cognitively challenging environments, participants sorted more when there were 18 alternatives than when there were six (3.67 vs. 1.57;  $F(1, 37) = 4.59, p < .05$ ). Replicating the results of Studies 1 and 2, participants sorted more when attributes were negatively correlated than when they were positively correlated (2.89 vs. 2.35;  $F(1, 37) = 11.05, p < .01$ ). Results also show a significant interaction between the number of alternatives and attribute correlations ( $F(1, 37) = 4.17, p < .05$ ), such that the difference in using sorting tools under negative correlation versus positive correlation was larger when there were 18 alternatives (4.11 vs. 3.23;  $F(1, 37) = 14.77, p < .0001$ ) than when there were six ( $F < 1$ ).

### 6.2.3 Objective Decision Quality

Providing additional support for Hypothesis 3, GEE repeated measures analysis with the range of expected values as a covariate shows a significant interaction between the availability of a sorting tool and the number of alternatives (Wald  $\chi^2(1, N = 740) = 11.44, p < .01$ ) such that the availability of sorting tools increased decision accuracy to a greater extent when there were 18 alternatives (.94 vs. .86;  $t(740) = 3.11, p < .01$ ) than when there were six (.96 vs. .93;  $t < 1$ ). As in Studies 1 and 2, there was an interaction between the availability of a sorting tool and attribute correlations (Wald  $\chi^2(1, N = 740) = 5.63, p < .05$ ) such that the availability of a sorting tool helped when attributes were positively correlated (.97 vs. .91;  $t(740) = 3.35, p < .01$ ) but not when attributes were negatively correlated (.90 vs. .91;  $t < 1$ ). As in Studies 1-2, decision accuracy was lower for negatively correlated choice sets than positively correlated choice sets (Wald  $\chi^2(1, N$



= 740) = 7.80,  $p < .01$ ). As the number of alternatives increased, decision accuracy also decreased (Wald  $\chi^2(1, N = 740) = 7.47, p < .01$ ). No significant main effect of sorting on decision accuracy was found ( $F < 1$ ).

Similar results were found for the choice probability measures. There was an interaction between the availability of a sorting tool and the number of alternatives on the chance-corrected probability of choosing the best alternative (Wald  $\chi^2(1, N = 148) = 14.31, p < .0001$ ) or one of the top three alternatives (Wald  $\chi^2(1, N = 148) = 9.44, p < .01$ ).<sup>3</sup> When there were 18 alternatives, the availability of a sorting tool increased the chance-corrected probability of choosing the best alternative (adjusted proportions = .39 and .28,  $z = 2.66, p < .01$ ) or one of the top three alternatives (adjusted proportions = .82 and .63,  $z = 3.41, p < .01$ ). When there were six alternatives, the availability of a sorting tool actually decreased the probability of choosing the best alternative (adjusted proportions = .59 and .73,  $z = -2.72, p < .01$ ) and had no significant effect on the probability of choosing one of the top three alternatives (adjusted proportions = .91 and .97,  $z = -1.08, ns$ ). As in Studies 1 and 2, there were significant interactions between the availability of a sorting tool and attribute correlations on the chance-corrected probability of choosing the best alternative (Wald  $\chi^2(1, N = 148) = 4.75, p < .05$ ) and the chance-corrected probability of choosing one of best alternatives (Wald  $\chi^2(1, N = 148) = 2.25, p < .07$ , one-tailed). When attributes were positively correlated, the availability of a sorting tool marginally increased the chance-corrected probability of choosing the best alternative (adjusted proportions = .56 and .50,  $z = 1.64, p < .06$ , one-tailed) and one of the top three alternatives (adjusted proportions = .95 and .83,  $z = 3.74, p < .0001$ ). When attributes were negatively correlated, the availability of a sorting tool decreased the

probability of choosing the best alternative (adjusted proportions = .41 and .51,  $z = -1.66$ ,  $p < .05$ , one-tailed) and had no significant effect on the probability of choosing one of the top three alternatives ( $z$ 's  $< 1$ ). Chance-corrected probabilities of choosing the best alternative (Wald  $\chi^2(1, N = 148) = 105.11$ ,  $p < .0001$ ) and one of top three alternatives (Wald  $\chi^2(1, N = 148) = 26.56$ ,  $p < .0001$ ) were higher when there were six than when there were 18 alternatives. As in Studies 1 and 2, probabilities of choosing the best alternative (Wald  $\chi^2(1, N = 148) = 4.63$ ,  $p < .05$ ) and one of top three alternatives (Wald  $\chi^2(1, N = 148) = 9.79$ ,  $p < .01$ ) were lower for negatively correlated choice sets than positively correlated ones. The availability of a sorting tool did not have a significant main effect on the likelihood that the best alternative or one of the best three alternatives was chosen.

#### **6.2.4 Subjective Decision Quality**

Analysis of the subjective decision quality measures revealed a three-way interaction between the availability of sorting tools, the number of alternatives, and attribute correlations ( $F(1, 70) = 5.27$ ,  $p < .05$ ). When there were six alternatives, the interaction between attribute correlation and availability of a sorting tool was not significant ( $F < 1$ ). However, when there were 18 alternatives, the availability of a sorting tool increased subjective decision quality when attributes were positively correlated but decreased it when they were negatively correlated ones ( $F(1, 70) = 8.52$ ,  $p < .01$ ). As with the objective quality measures, subjective decision quality was lower for negatively correlated than positively correlated choice sets (4.45 vs. 5.19;  $F(1, 70) = 131.42$ ,  $p < .0001$ ). Other effects were not significant.

### 6.3 Additional analyses

As in Studies 1.1 and 1.2, I examined how the use of an interactive restructuring tool affects decision quality. As in Studies 1.1 and 1.2, GEE repeated measures regression with the range of expected values analysis shows an interaction between attribute correlations and the number of sorts on relative accuracy (Wald  $\chi^2(9, N = 390) = 17.70, p < .05$ ). An increase in the number of sorts improved relative accuracy when attributes were positively correlated ( $\beta = .02$ , Wald  $\chi^2(1, N = 195) = 4.45, p < .05$ ) but decreased it when attributes were negatively correlated ( $\beta = -.13$ , Wald  $\chi^2(1, N = 195) = 8.71, p < .01$ ). As in Study 2, an increase in the number of sorts reduced relative accuracy overall ( $\beta = -.08$ , Wald  $\chi^2(12, N = 390) = 6.49E10, p < .0001$ ).

## **CHAPTER 7**

### **STUDY 1.4**

Studies 1.1-1.3 support the idea that interactive restructuring tools serve as substitutes for cognitive effort. The availability of a sorting tool reduces the amount of information that consumers evaluate and increases the use of compensatory decision strategies. In addition, consumers increase their use of interactive restructuring tools in cognitively challenging environments—such as when attributes are negatively correlated and when choice sets are large. However, the effects of this increased use of interactive restructuring tools on objective and subjective decision quality depend on the extent to which such tools effectively reduce the amount of information that needs to be evaluated. In particular, the availability of a sorting tool improves decision quality when attributes are positively correlated or choice sets are large but does not help when attributes are negatively correlated or choice sets are small. Interestingly, the subjective decision quality measures indicate that consumers realize (post-hoc) that interactive restructuring tools are less helpful when attributes are negatively correlated; yet their increased use of such tools under negative correlation suggests they are not always able to assess the a-priori benefits of interactive restructuring.

Importantly, Studies 1.1-1.3 also show that the overuse of interactive restructuring tools has detrimental effects on decision quality, particularly when attributes are negatively correlated. This suggests that the potential adverse effects of interactive restructuring tools may be overcome by limiting the amount of time available to use these

tools. Accordingly, Study 1.4 examines the effects of an interactive restructuring tool under time pressure and tests the following hypothesis:

**H4:** Under time pressure, the availability of an interactive restructuring tool increases decision quality under negative as well as positive correlation.

## 7.1 Experimental procedure

In Study 1.4, attribute correlation and the availability of an interactive restructuring tool were manipulated as in Studies 1.1-1.3. As in Studies 1.1 and 1.2, choice sets consisted of 18 alternatives defined by six attributes and participants made a practice choice followed by 10 actual decisions. In Study 1.4, participants were given 45 seconds to acquire information for each decision. A count-down timer indicated the remaining time. After this time, moving the mouse over a box no longer revealed information and participants were prompted to make a choice (see Figure 4). Dependent measures in Study 4 were identical to those of Study 1.3 (subjective decision quality measures' Cronbach alpha = .90). Fifty undergraduate students participated in the study for course credit.

**Time Remaining 0:32**

**Decision # 1**

Sort by: ☐ Monthly Rate of the ☐ Battery Life ☐ Warranty ☐ Weight ☐ Memory

Calculator	Monthly Rate of the	Battery Life	Warranty	Weight	Memory
A					
B					
C					
D					
E					
F					
G					
H					
I					
J					
K					
L					
M					
N					
O					
P					
Q					
R					

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the calculators (1 = worst and 100 = best).

**Please Choose One Calculator:**

A B C D E F G H I J K L M N O P Q R

**Questions:**

Question 1: How satisfied are you with the calculator you chose for your friend?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Satisfied

Question 2: How confident are you that you made the right choice?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Confident

Question 3: How hard was it to make this decision?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not hard Very hard

Question 4: If you had to search again for a calculator for this person in the future, what is the likelihood that you would use this site again to look for another calculator?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very likely

Question 5: Considering all calculators you looked at, how satisfied were you with this set of calculators, keeping in mind the preferences of your friend?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very satisfied

Question 6: How satisfied were you with the overall calculator search experience?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very satisfied

**Continue**



**Figure 4**

### **Study 1.4 Interface**

## **7.2 Results**

### **7.2.1 Information Acquisition and Decision Strategies**

Again supporting Hypothesis 1a, GLM repeated measures analysis shows that the availability of a sorting tool reduced the proportion of unique information examined (8.39% vs. 18.22%;  $F(1, 48) = 26.37, p < .0001$ ). There was a significant interaction between attribute correlation and the availability of a sorting tool ( $F(1, 48) = 4.91, p < .05$ ). As in the prior studies, the availability of a sorting tool reduced the proportion of unique information examined to a greater extent under positive correlation (7.35% vs. 17.89%;  $F(1, 48) = 35.81, p < .0001$ ) than under negative correlation (9.58% vs. 18.56%;  $F(1, 48) = 15.20, p < .0001$ ). Means for the dependent measures are presented in Table 4.

Among the 50 participants, four did not acquire enough information on at least one of the 10 choice sets to calculate the acquisition pattern. Again supporting Hypothesis 1b, results show that, even under time pressure, the availability of an interactive restructuring tool increased the use of compensatory decision strategies:

reducing the variance in acquisition time per attribute (3.36 vs. 9.38;  $F(1, 48) = 18.54, p < .0001$ ), marginally reducing the proportion of time on the most important attribute (.34 vs. .43;  $F(1, 48) = 2.57, p < .06$ , one-tailed), and increasing by-alternative processing (.28 vs. -.06;  $F(1, 44) = 6.94, p < .05$ ). Interactions between attribute correlation and the availability of a sorting tool were not significant.

**Table 4**  
**Study 1.4: Interactive Restructuring under Time Pressure**

Dependent measure	No sorting tool		Sorting tool available	
	Negative correlation	Positive correlation	Negative correlation	Positive correlation
Sorts	--	--	1.78	1.60
Objective decision quality	.68	.83	.76	.95
Probability of choosing the best alternative	.25 (31/125)	.45 (56/125)	.34 (43/125)	.61 (76/125)
Probability of choosing one of three best alternatives	.55 (69/125)	.68 (85/125)	.65 (81/125)	.91 (114/125)
Subjective decision quality	3.80	4.55	4.87	5.29
Unique cells examined (%)	18.56	17.89	9.58	7.35
Proportion of time on the most important attribute	.47	.43	.30	.30
Variance in proportion of time per attribute	10.83	7.92	4.67	2.05
Acquisition pattern	-.09	-.04	.22	.35

### 7.2.2 Use of Interactive Restructuring Tools

As expected, limiting the amount of time available for choice reduced differences in the amount of sorting under positive versus negative correlation. Under time pressure, for those who had a sorting tool available, there was no significant difference in the number of sorts for positively correlated sets than for negatively correlated ones (1.60 vs. 1.78;  $F(1, 24) = 2.07$ , ns).

### 7.2.3 Objective Decision Quality

Hypothesis 4 proposed that, under time pressure, the availability of a sorting tool would improve decision quality under negative as well as positive interattribute correlation. GEE repeated measures analysis with the range of expected values as a covariate shows a significant main effect of the availability of a sorting tool on relative accuracy, such that under time pressure the ability to sort increased decision accuracy (Wald  $\chi^2(1, N = 500) = 7.55$ ,  $p < .01$ ). Under time pressure, the interaction between attribute correlations and the availability of sorting tools was not significant (Wald  $\chi^2(1, N = 500) = 1.08$ ). In particular, the availability of a sorting tool helped when attributes were negatively correlated (.76 vs. .68;  $t(500) = 1.71$ ,  $p < .05$ , one-tailed) as well as when they were positively correlated (.95 vs. .83;  $t(500) = 3.28$ ,  $p < .01$ ). As in prior studies, decision accuracy was lower under negative than under positive correlation (Wald  $\chi^2(1, N = 500) = 62.42$ ,  $p < .0001$ ).

GEE repeated logistic regression results also shows a significant main effect of the availability of sorting on the probability of choosing the best alternative (Wald  $\chi^2(1, N = 500) = 6.82$ ,  $p < .01$ ) and one of the top three alternatives (Wald  $\chi^2(1, N = 500) = 7.77$ ,  $p < .01$ ). The interaction between interattribute correlation and the availability of sorting



did not significantly affect the probability of choosing the best alternative (Wald  $\chi^2(1, N = 500) < 1$ ) but did affect the probability of choosing one of the top three alternatives (Wald  $\chi^2(1, N = 500) = 8.85, p < .01$ ). The availability of a sorting tool increased the probability of choosing the best alternative when attributes were negatively correlated (proportions=.34 vs. .25;  $t(500) = 1.92, p < .05$ , one-tailed) as well as positively correlated (proportions=.61 vs. .45;  $t(500) = 2.42, p < .05$ ). However, as in the prior studies, the availability of a sorting tool increased the probability of choosing one of the top three alternatives to a greater extent when attributes were positively correlated (proportions = .91 vs. .68;  $z = 3.29, p < .01$ ) than under negative correlation ( $z = 1.28$ , ns). As in earlier studies, the probability of choosing the best (Wald  $\chi^2(1, N = 500) = 41.85, p < .0001$ ) or one of the top three alternatives (Wald  $\chi^2(1, N = 500) = 32.67, p < .0001$ ) was lower when attributes were negatively correlated.

#### **7.2.4 Subjective Decision Quality**

Consistent with the objective decision quality measures, GLM repeated measures analysis shows that the ability to sort increased consumers' evaluations of their choices (5.08 vs. 4.17;  $F(1, 48) = 14.52, p < .0001$ ). The interaction between attribute correlations and the availability of sorting was not significant ( $F(1, 48) = 2.68$ , ns). The availability of sorting increased subjective decision quality when attributes were negatively correlated (4.87 vs. 3.80;  $F(1, 48) = 15.69, p < .0001$ ) as well as positively correlated (5.29 vs. 4.55;  $F(1, 48) = 9.00, p < .01$ ). As with the objective measures, subjective evaluations of choice quality were lower under negative correlation than under positive correlation (4.34 vs. 4.92;  $F(1, 48) = 31.97, p < .0001$ ). In summary, I found support for Hypothesis 4 on all measures except the probability of choosing the top three alternatives.

## **CHAPTER 8**

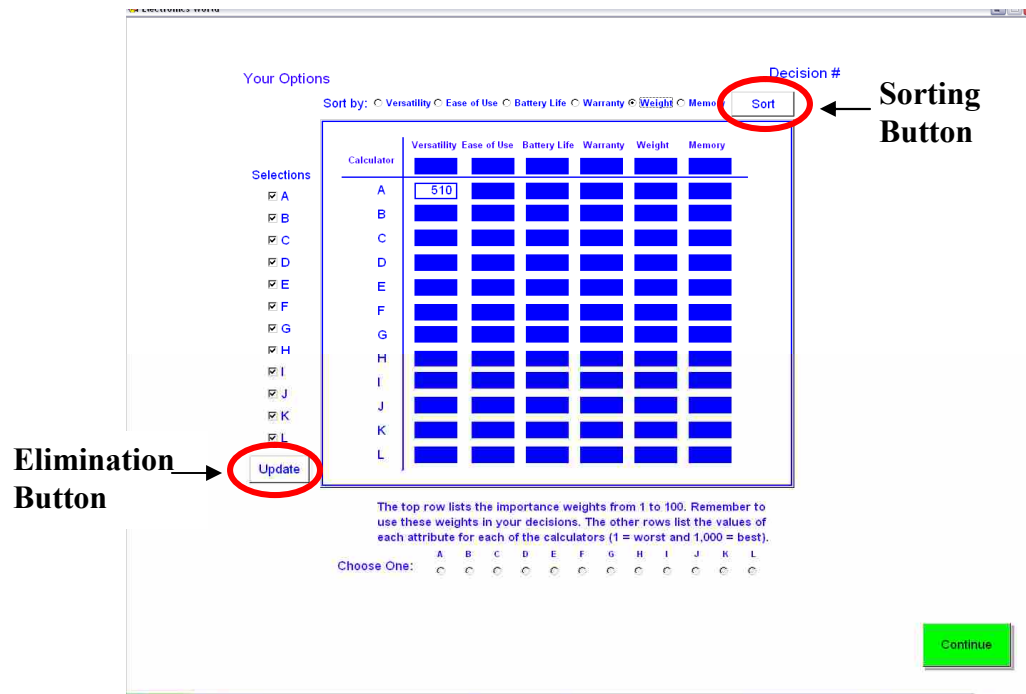
### **STUDY 5: THE IMPACT OF MULTIPLE RESTRUCTURING TOOLS**

Although sorting is one of the most commonly available interactive restructuring tools, many online environments also allow consumers to eliminate alternatives from consideration. The ability to eliminate, and its interaction with sorting, may have different effects on decision processes and outcomes (Todd and Benbasat 1991; 1992; 1999). In particular, because elimination tools allow consumers to remove less attractive options from consideration, they may be particularly helpful, and more likely to be used, in negatively correlated environments where simple sorts or scanning of values on the most important attribute will not clearly identify the best alternative. Accordingly, Study 1.5 examines elimination as well as sorting tools.

#### **8.1 Procedure**

Experimental variables in Study 1.5 were identical to those in Study 1.2, except that Study 1.5 also manipulated the presence of an elimination tool as a between subjects factor. To hide alternatives from view, participants for whom an elimination tool was available just needed to select one or more alternatives and then click the “update” button. Deselecting alternatives and clicking “update” restored those alternatives to view. Because pretesting suggested that having more than one interactive restructuring tool increased the perceived complexity of the decision task, the size of the choice set was reduced to 12 alternatives x 6 attributes (see Figure 5). Participants were randomly

assigned to one of the four between-subjects conditions. As in Studies 1.1-1.4, attribute correlation was manipulated within-subjects. Dependent measures in Study 1.5 were identical to those in Study 1.2, except that the number of alternatives eliminated was also recorded. Of the 122 participants, ten did not acquire enough information in at least one of the 10 choice sets to calculate their acquisition patterns.



**Figure 5**

## **Study 1.5 Interface**

## **8.2 Results**

Means for the dependent measures are presented in Table 5. One hundred twenty-two undergraduate students participated in this study. The mean quality of participants' choices was high ( $M = .85$ ). On average, participants acquired 19 pieces of unique information per choice set with an average time-per-acquisition of .49 seconds. When

sorting was available, participants sorted an average of 2.85 times per decision; when elimination was available, participants used this tool an average of 1.56 times per choice set and eliminated an average of 3.5 alternatives.

**Table 5**  
**Study 1.5: Multiple Restructuring Tools and Decision Processes**

Dependent measure	No sorting tool				Sorting tool			
	No elimination tool		Elimination tool		No elimination tool		Elimination tool	
	-	+	-	+	-	+	-	+
Sorts	--	--	--	--	1.83	1.58	4.53	3.39
Eliminations	--	--	1.73	1.29	--	--	1.85	1.39
Objective decision quality	.78	.93	.73	.91	.69	.94	.79	.95
Probability of choosing the best alternative <sup>a</sup>	.33 (53/160)	.65 (104/160)	.25 (38/155)	.65 (101/155)	.28 (41/145)	.66 (95/145)	.37 (55/150)	.68 (102/150)
Probability of choosing one of three best alternatives	.74 (118/160)	.94 (150/160)	.66 (102/155)	.90 (139/155)	.62 (90/145)	.92 (134/145)	.75 (112/150)	.92 (138/150)
Unique cells examined (%)	29.90	26.77	34.75	33.47	17.24	13.40	20.57	17.79
Proportion of time on the most important attribute	.60	.51	.58	.48	.41	.41	.41	.37
Variance in proportion of time per attribute	13.03	4.88	17.34	6.40	3.30	1.00	4.14	1.34
Acquisition pattern	-.12	-.07	-.28	-.18	.02	.09	-.04	.12

### 8.2.1 Information Acquisition and Decision Strategies

Providing additional support for Hypothesis 1a, that the availability of an interactive restructuring tool will reduce the amount of information examined, repeated-measures GLM analysis shows the presence of sorting tools led to a decrease in the percentage of unique cells examined (17.25% versus 31.23%;  $F(1, 118) = 62.02, p < .0001$ ). Unlike sorting tools, the presence of elimination tools led to an increase in the percentage of unique cells examined (26.64% versus 21.83%;  $F(1, 118) = 7.36, p < .01$ ).

Results also support Hypothesis 1b, that the availability of an interactive restructuring tool will increase the use of compensatory decision strategies. Results show that the presence of sorting tools: a) reduced the proportion of time spent on the most important attribute (.40 versus .54;  $F(1, 118) = 24.72, p < .0001$ ), b) reduced the variance in acquisition time per attribute (2.07 versus 9.16;  $F(1, 118) = 54.91, p < .0001$ ), and c) led to greater alternative-based processing (.04 versus -.16;  $F(1, 108) = 6.30, p < .05$ ).

Results provide mixed support for the idea that the effectiveness of interactive restructuring tools depends on choice context. In support, there was a significant interaction between attribute correlation and the availability of sorting tools ( $F(1, 118) = 10.62, p < .01$ ) in which the availability of sorting tools reduced the proportion of time spent on the most important attribute to a greater extent when attributes were negatively correlated (.41 versus .59;  $F(1, 118) = 32.17, p < .0001$ ) than when they were positively correlated (.39 versus .50;  $F(1, 118) = 12.83, p < .0001$ ). But, no significant interaction between attribute correlation and the availability of sorting tools on the percentage of unique information examined, variance in acquisition time per attribute, or acquisition patterns was found ( $F < 1$ ). The availability of elimination tools, and its interaction with

other experimental variables, had no significant effect on proportion of time on the most important attribute, variance in time per attribute, or acquisition patterns.

### **8.2.2 Use of Interactive Restructuring Tools**

Providing additional support for Hypothesis 2, GLM results show that participants sorted more often (3.18 versus 2.48;  $F(1, 57) = 11.60, p < .01$ ) and eliminated more often (1.79 versus 1.33;  $F(1, 59) = 10.06, p < .01$ ) when attributes were negatively correlated than when attributes were positively correlated.

### **8.2.3 Objective Decision Quality**

Providing additional support for Hypothesis 3, there was a significant interaction between interattribute correlation and the availability of a sorting tool (Wald  $\chi^2(1, N = 1220) = 5.14, p < .05$ ). Pairwise comparisons show that the sorting tool helped when attributes were positively correlated (.95 vs. .92;  $t(1220) = 1.52, p < .07$ , one-tailed) but not when they were negatively correlated (.74 vs. .76;  $t < 1$ ). In addition, GEE results show a significant interaction between the availability of a sorting tools and the availability of an elimination tool (Wald  $\chi^2(1, N = 1220) = 6.52, p < .05$ ) such that a sorting tool helped when a elimination tools was present (.82 vs. .86;  $t(1220) = 1.84, p < .04$ , one-tailed) but hurt when an elimination tool was absent (.87 vs. .82;  $t(1220) = 1.81, p < .04$ , one-tailed). Interestingly, there was also a significant three-way interaction between the availability of sorting tools, the availability of elimination tools, and attribute correlation (Wald  $\chi^2(1, N = 1220) = 9.78, p < .01$ ). Planned comparisons of the two-way interactions between sorting and elimination show that when attributes were negatively correlated, the availability of sorting tools increased decision quality when elimination tools were present but decreased decision quality when elimination tools were absent

(Wald  $\chi^2(1, N = 610) = 12.97, p < .0001$ ). However, when attributes were positively correlated, the availability of sorting tools increased decision quality regardless of the availability of elimination tools (Wald  $\chi^2(1, N = 610) < 1$ ). As in earlier Studies, decision quality was lower for negatively correlated than positively correlated choice sets (.75 versus .93; Wald  $\chi^2(1, N = 1220) = 336.87, p < .0001$ ). Other effects were not significant. Similar results were found in a repeated-measures GLM analysis that did not control for the range of expected values.

I found mixed results for the choice probability measure. GEE repeated logistic regression analyses revealed significant interaction between the availability of sorting tools and the availability of elimination tools on the probability of choosing the best alternative (Wald  $\chi^2(1, N = 1220) = 3.45, p < .05$ , one-tailed). Pairwise comparisons show that sorting tools increased the probability of choosing the best alternative when elimination tools were present (proportions = .53 vs. .44,  $z = 2.20, p < .05$ ) but not when elimination tools were absent (proportions = .46 vs. .49,  $z$ 's  $< 1$ ). Results also show a three-way interaction between the availability of sorting tools, the availability of elimination tools, and attribute correlation in terms of the probability of choosing the best alternative (Wald  $\chi^2(1, N = 1220) = 3.76, p < .05$ , one-tailed). Planned comparisons show that when attributes were negatively correlated, the availability of sorting tools increased the probability of choosing the best alternative when eliminations tools were present but decreased it when elimination tools were absent (Wald  $\chi^2(1, N = 610) = 7.82, p < .01$ ). However, when attributes were positively correlated, the availability of sorting tools increased the probability of choosing the best alternative regardless of the availability of elimination tools (Wald  $\chi^2(1, N = 610) < 1$ ). Finally, I found that the probability of

choosing the best alternative ( $\text{Wald } \chi^2(1, N = 1220) = 269.97, p < .0001$ ) or one of the top three alternatives ( $\text{Wald } \chi^2(1, N = 1220) = 75.92, p < .0001$ ), was higher when attribute correlations were positive than when they were negative. Other effects were not significant.

## **8.4 Discussion**

Results from Study 1.5 provide further insights into the effects of interactive restructuring on decision processes and outcomes. Consistent with the idea that consumers are more likely to use interactive restructuring tools in difficult choice environments, elimination as well as sorting tools were used more often when attributes were negatively correlated. Study 1.5 also replicates results from previous studies, showing that consumers change their decision strategies in the presence of sorting tools and that whether these changes lead to improvements in decision quality depends on decision context. Mixed support was found for the idea that attribute correlation moderates the effect of sorting on uses of decision strategies. In particular, although the effect of sorting on the proportion of time spent on the most important attribute was significantly reduced under negatively correlated environments, effects of sorting on the percentage of unique information examined, variance in acquisition time per attribute, or acquisition patterns were not significantly affected by attribute correlation.

Results from Study 1.5 also suggest that the effects of interactive restructuring tools on decision making vary by the types of tools that marketers make available to consumers. For example, unlike sorting, the availability of elimination increases, rather than reduces, the percentage of unique information acquired. The three-way interaction



between the availability of sorting, the availability of elimination, and attribute correlation on decision quality found in Study 1.5 also illustrates the contingent effects of interactive restructuring tools. In particular, Study 1.5 replicates earlier results that the availability of sorting only helps decision quality when attributes were positively correlated. However, results also show that the availability of sorting can sometime hurt decision quality. In Study 1.5 the availability of sorting, without the ability to eliminate, hurts in negatively correlated environments. Yet, when both tools are available, decision making improves in negatively correlated environments.

An explanation for these results is that eliminating low quality alternatives on an attribute after an initial sort means that subsequent sorting on other attributes increases the probability that the best alternative is listed on the top of a choice set under negative correlation. Applying such a strategy to the choice sets in Study 1.5 (see Appendix A) shows that, in negatively correlated environments, when both sorting and elimination tools are available, the probability that the best alternative is listed at the top of a choice set is 60% versus 20% when only sorting is available. However, under positively correlated environments, the probability that the best alternative is listed first is 60% regardless of whether elimination is available.

## **CHAPTER 9**

### **GENERAL DISCUSSION**

#### **9.1 Summary and theoretical implications**

The use of easy-to-use interactive restructuring tools offers consumers a greater role in the creation of information environments (Hoffman and Novak 1996). In theory, this should allow them to make better decisions and increase their confidence in these decisions (Lurie and Mason 2007). However our results suggest that although interactive restructuring tools can help consumers make better decisions, particularly when product attributes are positively correlated and choice sets are large, they fail to improve decision quality when attributes are negatively correlated or choice sets are small. Indeed our results suggest that, in employing interactive restructuring tools as substitutes for cognitive effort, consumers may overuse these tools with negative implications for decision quality.

Study 1.1 supports the idea that interactive restructuring tools serve as substitutes for cognitive effort and shows that sorting increases when attributes are negatively correlated and evaluating alternatives is more challenging. In addition, the availability of sorting improves decision quality when attributes are positively correlated but not when attributes are negatively correlated. In fact, increased tool use under negative correlation leads to declines in decision quality. Study 1.2 replicates and extends these results to show that the presence of an interactive sorting tool reduces the amount of unique information acquired and increases the use of compensatory decision processes.

Study 1.3 extends the results of studies 1.1 and 1.2 to show that consumers increase their use of restructuring tools when faced with larger choice sets and that the

availability of interactive restructuring tools improves decision quality to a greater extent for larger relative to smaller choice sets. Study 1.3 also shows that results for subjective measures of choice quality reflect objective ones. In addition, Study 1.3 provides further evidence that increased use of interactive restructuring tools hurts decision quality when attributes are negatively correlated.

Given that Studies 1.1-1.3 suggest that consumers tend to overuse sorting tools in environments in which attributes are negatively correlated, Study 1.4 tests the idea that reducing tool usage through time pressure will increase the effectiveness of such tools under negative correlation. Results from Study 1.4 show that time pressure effectively reduces sorting under negative correlation to that observed under positive correlation. Under time pressure, with the exception of the probability of choosing one of the best three alternatives, the availability of sorting improves objective and subjective decision quality under negative as well as positive correlation.

Study 1.5 extends studies 1.1-1.4 examination of single interactive restructuring tool to explore the effects of elimination as well as sorting tools on decision-making. Because elimination tools allow consumers to remove less attractive options from consideration, they may be particularly helpful in negatively correlated environments where simple sorts or scanning of values on the most important attribute will not clearly identify the best alternative. Results from study 1.5 replicate the finding that interactive restructuring tools serve as substitutes for cognitive effort and show that both sorting and elimination increase when attributes are negatively correlated. Further, study 1.5 suggests that the effects of interactive restructuring tools on decision making vary by the types of tools that marketers make available to consumers. For example, when attributes are

negatively correlated, the ability to sort can lower decision quality when elimination tools are unavailable but increase decision quality when elimination tools are available.

However, when attributes are positively correlated, the ability to sort improves decision quality regardless of the availability of elimination tools.

From a theoretical standpoint, these results are interesting because although they clearly show adaptive behavior, both in the use of interactive restructuring tools as well as in decision processes, it appears that providing consumers with tools that allow them to easily restructure information environments does not always lead to better decisions. For example, although consumers clearly engage in different decision processes and tool use under negatively correlated environments versus positively correlated environments when having access to these tools, these differences do not lead to enhanced performance. It is interesting to compare these results, showing that consumers search too little after sorting on an attribute, with Diehl's (2005) results showing that consumers search too much when alternatives are sorted by a recommendation agent based on expected utility. Both suggest that consumers may have difficulty assessing how well different tools meet their needs in varying contexts.

## **9.2 Managerial implications**

Although interactive restructuring tools have the potential to reduce information overload and improve decision quality, results showing harmful as well as helpful effects of such tools suggest that care be employed in their use. In particular, it is important for marketers to consider the implications of providing such tools to consumers. Our results suggest that consumers may overuse restructuring tools—with negative consequences for

objective and subjective decision quality. This suggests that marketers may better serve consumers by limiting the use of such tools and encouraging consumers to not over rely on such tools to help them make decisions. Although time pressure is one way to do this, a more practical approach is to subtly remove restructuring tools after they are first used. For example, after an initial sort, consumers might be provided with a new display in which sorting is no longer available. Alternatively, an initial sort of a product matrix could lead to detailed information grouped by alternative rather than a matrix in which additional by-attribute comparisons (and sorting) are discouraged.

### **9.3 Limitations and future research**

It is important to point out two of the limitations of this work. First, the convenience samples used are not representative of the U.S. population as a whole. Second, for experimental control, these studies were limited to a particular product category of interest to our participants and lacked much of the richness of real websites. Future research could seek to address these issues, perhaps examining the use of interactive restructuring tools on commercial websites.

As in the real world, our experiments provided little feedback to consumers on the quality of their decisions—although the match between subjective and objective quality measures suggests that consumers have a good sense of their performance. It would be interesting to examine whether outcome feedback alone might mitigate the overuse of restructuring tools I observe or whether extensive cognitive feedback is necessary for consumers to realize how to best use such tools in different environments (Balzer, Doherty, and O'Connor 1989). In addition, although our studies used agent tasks, in

which consumer preferences are fixed, to examine how interactive restructuring tools affect decision quality, future research could examine how interactive restructuring tools affect the construction of consumer preferences in addition to reflecting pre-existing preferences (Bettman, Luce, and Payne 1998).

Future research could also study the effects of different types of restructuring tools on decision making. For example, the effects of elimination tools could be compared with those of tool for selecting alternatives to consider. Given that selection generally leads to smaller consideration sets than elimination (Levin, Jasper, and Forbes 1998), consumers may employ different decision processes when using such tools. As new technologies continue to blur the boundaries between computer and consumer information processing, it is important to test the implications for human behavior.

## NOTES

<sup>1</sup> Whether attributes are positively or negatively correlated depends on characteristics of the marketplace and which attributes a consumer uses. Buyers of luxury cars will find that seating room, horsepower, and quiet operation are usually positively correlated; while those seeking hotel rooms often find they need to make tradeoffs between location and room size.

<sup>2</sup> I modified the SPSS code available at <http://www.spsstools.net/Syntax/Bootstrap/GeneratingMVNwithSpecifiedCorrelationMatrix.txt>. Following Bettman et al. (1993), an average interattribute correlation of .60 was chosen for the positive sets and an average interattribute correlation of -.20 was chosen for the negative sets since it is the lowest possible correlation obtainable given six attributes (Bettman et al. 1993). For the positive sets, the average correlation among the attribute pairs was .61. The maximum pairwise attribute correlation in a set averaged .78, and the minimum pairwise correlation averaged .42. For the negative sets, the average correlation among attribute pairs was -.19. The most negative pairwise attribute correlation in a set averaged -.57, and the least negative pairwise correlation averaged -.09.

<sup>3</sup> Following Malhotra (1982), for each participant I determined the chance-corrected probability of choosing the best or one of the three best alternatives under positive versus negative correlation as  $\bar{p}_i = (p_i - p_{ic}) / (1 - p_{ic})$ , where  $\bar{p}_i$  = the proportion of correct choice adjusted for chance,  $p_{ic}$  = proportion of correct choice by chance alone, and  $p_i$  = the observed proportion of correct choice unadjusted for chance

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factors. Thus, two chance-corrected probabilities were calculated for each participant for each measure.



## **PART TWO**

### **VISUAL AND COGNITIVE WALLS: IMPLICATIONS FOR CONSUMER PREFERENCES AND CONSUMER CHOICES**

## **CHAPTER 10**

### **INTRODUCTION TO PART TWO**

Whether it's browsing thousands of digital cameras on eBay or making sense of a myriad number of coffee makers on Amazon.com, it is clear that today's consumers face large amounts of information. Online retailers have tried many approaches to help consumers deal with increasing amounts of information including electronic agents that recommend particular products based on consumer preferences or the similarity of their shopping histories to other consumers (Diehl 2005; Häubl and Murray 2003); presenting information in matrix format, that allows alternatives and attributes to easily be compared (Häubl and Trifts 2000); and providing tools for sorting, selecting, and filtering alternatives (Lurie, Wen, and Song 2010; Todd and Benbasat 1991; 1992; 1999).

Prior research suggests that the navigability of a retail website is a key determinant of the likelihood that browsers turn into buyers, the extent to which they learn to efficiently use the website, and the likelihood they return to the website for future purchases (Johnson, Bellman, and Lohse 2003; Nielsen 1993; Palmer 2002). One widely used approach to improve navigability is to use visual separators such as bars, lines, boxes or different colors between rows or between columns in a product matrix. For example, both homedepot.com and radioshack.com display alternatives in columns and attributes in rows on their websites but homedepot.com uses vertical lines to separate alternatives while radioshack.com uses horizontal lines to separate attributes (see Figure 6). It is unclear which is better from a decision-making perspective.

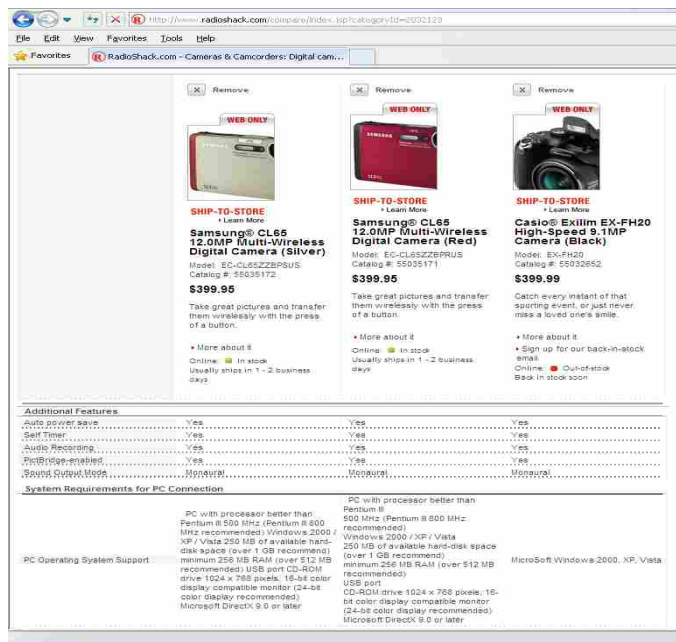
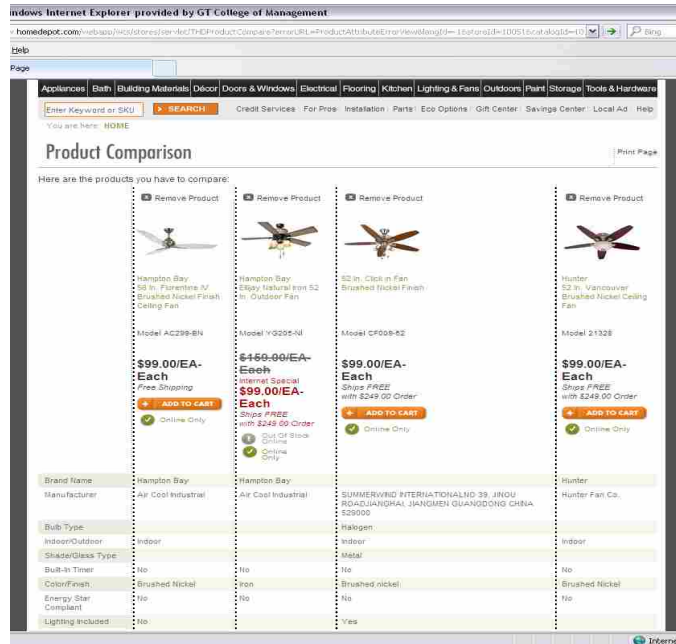


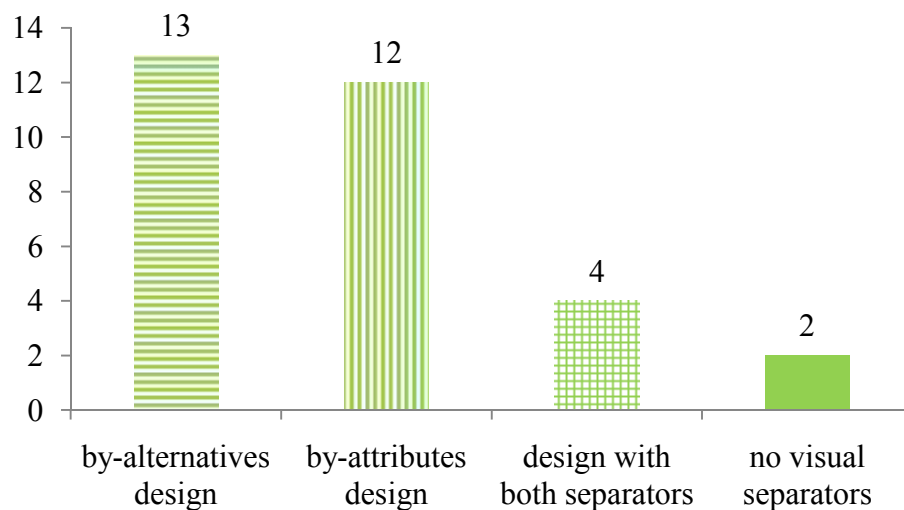
Figure 6

Examples of Visual Separators Used By Online Retailers

In order to explore whether and how real online retailers use those visual separators such as lines between product alternatives or product attributes on their websites, we examined the visual design of the top 100 shopping web sites in 2009. This website ranking is released by Alexa, a Web Information Company providing information about websites including top sites, internet traffic Stats and metrics, and online reviews. Of the top 100 shopping web sites, we focused on 31 sites, on which consumers can directly compare several different product options. Among these 31 shopping sites, the percentage of sites using lines between product alternatives is not significantly different from those using lines between product attributes (42% vs. 39%;  $z = .02$ , ns). The percentage of sites having lines between both product alternatives and attributes is significantly lower than that having lines either between alternatives (13% vs. 42%;  $z = 2.28$ ,  $p < .05$ ) or attributes (13% vs. 39%;  $z = 2.05$ ,  $p < .05$ ); and the percentage of sites having no lines in the product comparison matrix is also significantly lower than that having lines either between alternatives (6% vs. 42%;  $z = 3.01$ ,  $p < .01$ ) or attributes (6% vs. 39%;  $z = 2.80$ ,  $p < .01$ ) (see Figure 7). These results suggest that visual separators between product alternatives and these between product attributes are two widely used visual-design approaches by real online retailers, but it is unclear which one is better from a consumer decision-making perspective.

An important research idea proposed in this article is that those widely used visual design elements may have an *unintentional* impact on consumer behavior. From a visual-design perspective, most assessments of website design involve usability testing, with a focus on user understanding, the extent to which users get lost, and the speed of information retrieval (Huizingh 2000; Nielsen 1993; Palmer 2002). Thus, these visual

separators are widely used to improve web usability and navigability. However, in contrast, a large body of decision making literature tends to examine how task aspects of a decision environment, such as the amount of information in a choice set; or context aspects, such as the correlation among product attributes, affect decision processes and outcomes (Bettman, Johnson, Luce, and Payne 1993; Payne, Bettman, and Johnson 1993; Lurie 2004). Similarly, research on consumer preferences focuses on exploring how evaluation modes, such as choice versus judgment (Lichtenstein and Slovic 1971), choice versus matching (Tversky, Sattath, and Slovic 1988), or joint versus separate evaluations of alternatives (Hsee 1996) affect and even reverse preferences. In general, there has been little examination of how visual design elements, that make no changes to task or context variables or evaluation modes, may affect consumer preferences and decision making.



**Figure 7**

**Visual Design of Top 31 Shopping Websites**

This article proposes that seemingly innocuous design elements, such as visual separators, act as cognitive constraints that systematically affect the acquisition and processing of information and evaluability of attributes with implications for preferences, decision processes, and decision outcomes. To the extent that consumers adapt their decision processes to task and context variables in the decision environment (Bettman et al. 1993; Payne, Bettman, and Johnson 1988; Payne, Bettman, and Johnson 1993), visual separators may change consumers' adaptivity to the decision environment through encouraging particular types of information processing. By encouraging the uniform use of particular information acquisition strategies, visual separators should also serve to enhance decision efficiency such as increasing processing speed because they enable consumers to process information in a more systematical way. To the extent that decision processes have a larger impact on choice quality in environments where consumers need to make tradeoffs among attributes (Bettman et al. 1993; Payne et al. 1988), we expect that visual separators will have the greatest effect on choice quality in such environments such that when visual separators encourage the use of decision strategies that fit with the decision context, they will improve choice quality while when visual separators encourage the use decision strategies that do not fit with the context, they will hurt choice quality.

In a series of studies we examine how visual separators affect decision processes and outcomes in different choice contexts. Study 1 demonstrates that visual separators can lead to preference reversals. Studies 2 and 3 show that visual separators affect decision processes and outcomes but that these effects depend on the characteristics of the decision context; in particular, the intercorrelation among product attributes. When

product attributes are negatively correlated, visual separators between alternatives improve decision quality whereas those between attributes hurt decision quality. However, when product attributes are positively correlated, visual separators do not affect choice quality. Process tracing results show that visual separators between attributes augment by-attribute processing under positive correlation and visual separators between alternatives augment by-alternative processing under negative correlation and reduce the extent to which consumers adapt their choice processes to the choice context. In addition, visual separators enhance decision efficiency. Study 4 shows that under time pressure, visual separators between attributes as well as alternatives improve decision quality when product attributes are negatively correlated.

By examining how visual aspects of electronic environments affect consumer preferences, decision processes, and decision outcomes, this article provides a link between research on design and usability of information environments (Huizingh 2000; Nielsen 1993) and research on preferences and decision making (Bettman et al. 1993; Payne et al. 1988; Payne et al. 1993). More generally, this research adds to our understanding about the link between perception and cognition (Fiske 1993; Johnson et al. 2003), with implications for preference reversals and consumer decision-making. From a managerial perspective, this research provides insights into how seemingly innocuous design changes may affect consumer decision making and when visual separators are likely to be helpful or harmful to consumers.

## **CHAPTER 11**

### **VISUAL DESIGN IN CHOICE ENVIRONMENTS**

There are many factors that affect the visual appeal and navigability of choice environments. These include information presentation style, color, size, brightness, font and shape, and graphics and animation (see Nielsen 1993; 2000 for reviews). In this article, we focus on a particular design element with potentially important implications for decision making, the use of visual separators. We use the term “visual separators” to refer to design features such as bars, lines, boxes, or different colors in the decision environment that can change consumers’ perception of the presentation of information. Examples of visual separators include graphical objects, such as boxes and lines that divide different pieces of data, and shadows and highlights that separate information into groups. Visual separators are widely used in both online and offline environments. In traditional environments, retail stores often display a brand in the shelf either in a vertical or horizontal way which might influence quality expectations and consumer choices (Chandon et al. 2009; Raghubir and Valenzuela 2008). Similarly, many online retailers display products with lines separating alternatives or colors highlighting differences among choice options. Despite their widespread employment, the impact of visual separators on consumer decision-making is unclear. Research on visual design and decision making offer related but somewhat different perspectives on how visual separators may affect consumer behaviors such that visual design research focuses on examining the effect of visual elements on usability and navigability of an interface which in turn affects performance while decision literature tends to explore making no



changes to task or context variables, how visual separators affect consumers' adaptive behaviors and decision making.

### **11.1 The Visual Design Perspective**

From a visual design perspective, visual separators between attributes or alternatives in a product matrix may increase users' understanding of the decision environment and make navigation easier. The gestalt principle (Rock and Palmer 1990) suggests that things are perceived to belong together as a group if they are close together. Therefore, enclosing information by lines or boxes enhances perceived closeness, creating a dialogue for human-computer interaction and potentially leading to performance improvements (Nielsen 1993; Took 1990). Visual design literature has shown great performance improvements in information search tasks such as reduced time of completing a task, reduced number of errors made by users while performing the task, or increased number of tasks completed per unit time after making improvements to user-centered navigability through good interface design (Nielsen 2000; Nielsen and Levy 1994). For example, Palmer (2002) suggests that web site success such as user satisfaction, the likelihood of return, and the frequency of use is associated with design elements like organization, arrangement, or layout of an interface. Overall, visual design research suggests that web design elements, such as visual separators in a product matrix, are associated with performance improvement (Nielsen 1993; 2000; Palmer 2002; Took 1990).

## **11.2 The Decision-Making Perspective**

Instead of examining on design elements and its impact on the usability of a site and user performance, research on decision-making focuses on the links among characteristics of the particular problem facing the decision maker, decision processes in response to those characteristics, and choice quality. On the one hand, this research has shown that visual design elements in the environments can have an influence on consumer behaviors. For example, visual primes such as changing the background picture and colors of a web page can produce changes in consumer choices because priming can influence external information search (Mandel and Johnson 2002). Different colors of the background such as blue versus red may activate different levels of goals, avoidance vs. approach, which in turn can enhance human performance on detailed-oriented versus creative cognitive tasks (Mehta and Zhu 2009). On the other hand, this research shows that consumers adapt their decision processes and choices to task and context characteristics of the decision environment including the ease with which particular attributes can be compared (Lynch and Ariely 2000), whether information is organized or displayed by alternative or by attribute (Jarvenpaa 1989, Tabatabaei 2002), or the extent to which consumers need to trade off different attributes (Bettman et al. 1993). For example, making quality versus price information easier to process can increase the use of quality information in choice (Lynch and Ariely 2000); organizing information by alternative leads to greater by-alternative processing, as do choice tasks in which product attributes are negatively correlated with one another (Bettman et al. 1993; Jarvenpaa 1989; Tabatabaei 2002). Other research has shown that structural aspects of information,

such as the distribution of attribute levels across alternatives, can affect the effort and accuracy of choice (Lurie 2004).

In summary, the visual design and decision research have important but different perspectives on the impact of visual separators on decision-making. While the visual design perspective proposes that visual separators, that improve navigability and interactivity, will enhance human performance, the decision perspective suggests that those improvements will depend on the characteristics of the decision environment.

## **CHAPTER 12**

### **VISUAL SEPARATORS AND DECISION MAKING**

Psychology literature has shown that visual elements such as lines, colors, bars, or texture can perceptually group separate items and if separate items are perceptually grouped, attention will be directed to groups rather than to single items (Treisman and Gelade 1980; Treisman 1982). According to the gestalt principle (Rock and Palmer 1990), things are perceived to belong together as a group if they are close together. Relatedly, attention research suggests that eye movements are guided by the information's spatial arrangement (Duncan and Humphreys; Rayner 1998; van der Lans et al. 2008). Further, research has shown that perceptually visual search takes place in two successive stages. The first stage is the preattentive stage in which the field is segmented into separate objects on the basis of Gestalt properties such as spatial proximity, continuity of contour, or shared color or movement. The second stage is the focal attention where a particular object is analyzed in more detail (Neisser 1967). That is, preattentive processes serve to segment the field into separate objects, followed by a focal attention that deals with only one object at a time (Duncan 1984). All of these suggest that lines separating alternatives in the choice set can create a by-alternative grouping and lead to a visual searching on different choice alternatives (i.e., a by-alternative processing). Similarly, lines separating attributes in the choice set can create a by-attribute grouping and lead to a visual searching on different attributes of the same alternative (i.e., a by-attribute processing).

In thinking about how visual separators are likely to affect decision making, it is important to examine the effect of those visual separators on consumer preferences. Prior

research has shown that evaluation mode, for instance, whether two choices are presented and evaluated side by side or they are presented and evaluated separately (i.e., joint versus separate evaluation) will lead to preference reversals (Hsee 1996). Based on the preceding discussion, because visual separators encourage particular types of information processing (e.g., by-alternative or by-attribute processing) by segmenting the interface into a by-alternative grouping or a by-attribute grouping, visual separators between choice alternatives will be more likely to lead consumers to evaluate alternatives *separately* while visual separators between attributes will be more likely to lead consumers to evaluate alternatives *jointly*. According to the evaluability hypothesis (Hsee 1996), in the separate evaluation mode, people base their evaluation primarily on the easy-to-evaluate attribute alone because they don't know how to evaluate an option's value on the hard-to-evaluate attribute. However, in the joint evaluation mode, people could compare one option against the other and this comparison would increase the evaluability of the otherwise hard-to-evaluate attribute. In short, separate evaluation is determined chiefly by the easy-to-evaluate attribute while joint evaluation is influenced by both the hard-to-evaluate attribute and the easy-to-evaluate attributes. Therefore, when a choice involves a trade-off between a hard-to-evaluate attribute and an easy-to-evaluate attribute, the easy-to-evaluate attribute has a greater impact when visual separators are between choice alternatives than when they are between attributes—preference reversals occur.

**H1:** Other things being equal, visual separators between choice alternatives lead to a preference for the choice superior on the easy-to-evaluate

attribute while visual separators between attributes lead to a preference for the choice superior on the hard-to-evaluate attribute.

Further, decision research shows that decision makers adaptively respond to the choice context, such as intercorrelation among product attributes (Bettman et al. 1993). When attributes are negatively correlated, decision makers are more likely to use compensatory decision making strategies, in which multiple attributes are considered at a time, because the gains in accuracy outweigh the additional effort involved in using such strategies. However, when attributes are positively correlated, consumers are more likely to employ heuristics because in such environments, heuristic strategies involve less effort yet may lead to high quality choices. For instance, decision makers show adaptivity by shifting their information processing pattern such that they engage in more by-alternative processing under negatively correlated environments and more by-attribute processing under positively correlated environments (Bettman et al. 1993).

By encouraging particular types of information processing (e.g., by-alternative or by-attribute), visual separators may interrupt consumers' adaptivity to the decision environment. For example, because lines between choice alternatives create a by-alternative grouping, one has to go beyond these lines to process information of the same attribute but a different alternative. Similarly, because lines between attributes create a by-attribute grouping, one has to go beyond these lines to process information of the same alternative but a different attribute. In other words, visual separators are likely to reduce adaptivity to the choice context, for instance, reduce shifts in information acquisition patterns under positive vs. negative correlation among attributes. This

suggests that, when visual separators are present, differences in information acquisition patterns under negatively correlated environments and positively correlated environments should be smaller compared to when there are no visual separators in the information environment.

**H2:** Visual separators will reduce adaptivity to the decision context such that differences in information acquisition patterns under positively correlated environments versus negatively correlated environments will be smaller when visual separators are present.

Relatedly, research has shown that a match between decision aids and the context of decision environments facilitates decision-making processes, especially when people have an inclination to use the specific types of decision strategies under certain decision environments (Hoch and Schkade 1996). Under negatively correlated environments in which compensatory decision strategies are more likely to be used and have a great impact on decision quality, because visual separators between alternatives fit with compensatory decision processes while visual separators between attributes do not, those between alternatives should improve decision efficiency such as facilitate information processing or increase processing speed, whereas visual separators between attributes should reduce decision efficiency such as impede information processing or decrease processing speed in such environments. However, under positively correlated environments, because different types of decision processes are less impactful on decision quality, visual separators should always be able to make decision making more

efficient and increase processing speed compared to there are no visual separators in such environments, regardless of the fit of visual separators with decision processes.

**H3:** When attributes are negatively correlated, visual separators between alternatives will increase decision efficiency while those between attributes will decrease decision efficiency. When attributes are positively correlated, visual separators will always increase decision efficiency.

Because visual separators encourage particular types of information processing (e.g., by-alternative or by-attribute processing), the impact of visual separators on choice quality is likely to depend on the fit between decision processes they encourage and the choice context. For example, if a choice context requires decision makers to make tradeoffs among attributes to make good decisions, such as when attributes are negatively correlated with one another (Bettman et al. 1993), decision quality should be enhanced by separators between alternatives since they encourage non-compensatory (i.e., by-alternative) processing. In contrast, when tradeoffs among attributes are required, visual separators between attributes should lower choice quality because they will encourage non-compensatory (i.e., by-attribute) decision processes. However, because decision processes have less impact on decision quality in positively correlated environments, because decision makers do not need to make tradeoffs among attributes (Bettman et al. 1993), the effect of visual separators on decision outcomes should be limited in such environments.

Therefore, we predict that:



**H4:** Visual separators and choice context will interact to affect decision quality:

- (a) When attributes are negatively correlated, visual separators between alternatives will increase decision quality while those between attributes will decrease decision quality;
- (b) When attributes are positively correlated, the effects of visual separators on choice quality will be reduced.

Study 2.1 tests Hypothesis 1 by examining whether visual separators will lead to preference reversals. Study 2.2 tests Hypothesis 4 by examining whether the effect of visual separators on decision quality depends on choice context. Study 2.3 extends Study 2.2 to test Hypotheses 2- 4 by examining whether visual separators affect decision processes and decision efficiency depending on choice context.

## **CHAPTER 13**

### **STUDY 2.1**

#### **13.1 Method and Procedure**

Participants (48 undergraduate students) received \$10 for participating in a study in which they were asked to assume that they were music majors and were looking for a music dictionary in a used store. They planned to spend between \$20 and \$60 on the dictionary. They were then presented with descriptions of two music dictionaries adapted from Hsee 1996 (study 1). Each of two dictionary options consisted of three attributes (year of publication, number of entries, and presence of defects). Among three attributes, year of publication is a common attribute, number of entries is a hard-to-evaluate attribute, and presence of defects is an easy-to-evaluate attribute. Participants were instructed to take as much time as they wished to review the information of each dictionary and were asked to indicate how much they were willing to pay for each dictionary. Hsee (1996) manipulated a between-subjects factor, separate vs. joint evaluation mode. In the separate condition, participants were presented with the information on one of two dictionaries and in the joint condition, participants were presented with the information on both dictionaries. Hsee (1996) found that in the joint condition, willingness to pay for the dictionary with greater hard-to-evaluate attribute was relatively higher. However, in the separate condition, willingness to pay for the dictionary with greater easy-to-evaluate attribute was relatively higher. In this article, I did not manipulate the evaluate mode and only used the joint evaluation mode with visual separators, between alternatives vs. between attributes, as a between-subjects factor.

## **13.2 Experimental Variables**

### **13.2.1 Visual Separators**

Visual separators were manipulated through lines separating alternatives or lines separating attributes in the choice set.

### **13.2.2 Information Display**

To control for potential effects of displaying alternatives in rows versus columns, half of the participants made choices from displays in which alternatives were displayed in rows and attributes were displayed in columns and half made choices from displays in which alternatives were displayed in columns and attributes were displayed in rows.

Other aspects of the interface were identical across conditions.

Overall, this study uses a 2 (Visual separator: lines separating alternatives vs. lines separating attributes) x 2 (Information display: alternatives in rows and attributes in columns vs. alternatives in columns and attributes in rows) between-subjects design. All participants were randomly assigned to one of four conditions.

## **13.3 Dependent Variables**

After examining information about the two dictionaries, participants were asked to indicate how much they were willing to pay for each dictionary.

## **13.4 Results**

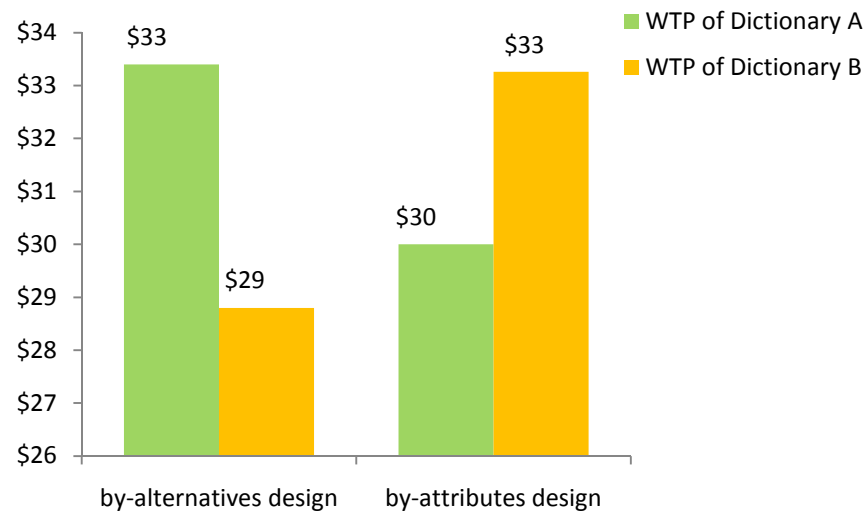
Participant's willingness to pay for the two dictionaries in the different experimental conditions are summarized in Figure 8. There were no significant effects of information display (i.e., whether products were displayed in columns or in rows) on

willingness to pay, so results were collapsed across display conditions. In support of Hypothesis 1, as the Figure 8 shows, preferences were dramatically different depending on whether lines separated alternatives or attributes. When lines separated alternatives, willingness to pay was higher for dictionary A (with greater easy-to-evaluate attribute value) than for dictionary B (\$33.40 vs. \$28.80,  $F(1, 24) = 4.17, p < .05$ , one-tailed), but when lines separated attributes, willingness to pay was lower for dictionary A than for dictionary B (with greater hard-to-evaluate attribute value) (\$30.00 vs. \$33.26,  $F(1, 22) = 7.15, p < .05$ ). To assess the preference reversal effect, we compared the difference between the willingness to pay for dictionary A and B in the lines separating alternatives condition with that in the lines separating attribute condition (Hsee 1996). The preference reversal was significant (4.60 vs. -3.26,  $F(1, 47) = 8.96, p < .01$ ).

Study 2.1 shows that visual separators have an impact on consumer preferences, and in particular, lead to preference reversals such that when visual separators are between product options, people are willing to pay more for an option superior on the easy-to-evaluate attribute, whereas when visual separators are between product attributes, they are willing to pay more for an option superior on the hard-to-evaluate attribute. According to the evaluability hypothesis (Hsee 1996), separate evaluation is determined chiefly by the easy-to-evaluate attribute while joint evaluation is influenced by both the hard-to-evaluate attribute and the easy-to-evaluate attributes—because lines between alternatives separate choices while lines between attributes joint choices, those visual separators lead to preference reversals.

The purpose of Study 2.1 is to explore the effect of visual design elements on consumer preferences. Study 2.1 confirms that visual separators have a significant

influence on consumer behaviors and reverse their preferences without making any changes to the context or task variables in the decision environments. The unanswered questions are how those visual elements might affect consumer choices? Will they always improve choice quality? Study 2.2 is designed to examine how visual design elements interact with decision contexts to affect consumer choices.



**Figure 8**

**Study 2.1: The Effect of Visual Design on Preferences**

## **CHAPTER 14**

### **STUDY 2.2**

#### **14.1 Method and Procedure**

Participants (85 undergraduate students) received course credit for participating in a study in which they were asked to imagine they were buying a coffee maker for a friend's wedding and had decided to order the coffee maker from an online retailer of consumer electronics, Kitchen USA. They were told that all of the coffee makers cost \$59.95, which was within their budget.

Next, participants were told that a recent article in Consumer Reports suggested that there were several attributes they should consider when buying a coffee maker: material, ease of use, durability, warranty, settings, and size. All attributes were rated from 1 to 1000 with 1 as the worst and 1000 as the best. To help participants in their decisions, their friend had indicated the importance of these attributes on a scale from 1 to 100, where 100 was the most important and the sum of the attributes was 100. Participants were told to use these weights in their decisions. This agent task provides a normative sense of choice goodness and avoids potential measurement errors associated with using participants' own preferences to determine the best choice (Payne et al. 1993).

Following previous research (Bettman et al. 1993), attribute values were randomly generated from a multivariate normal distribution that ranged from 1 to 1000 such that attribute correlations were either positive or negative. Prior research has shown that decision makers use different strategies under positive versus negative correlation regardless of whether or not these correlations are made explicit (Bettman et al. 1993). Attribute weights were randomly chosen from a uniform distribution and rescaled to sum

to 100. Each choice set was presented as a six by six matrix with alternatives in rows and attributes in columns, as in previous research (Bettman et al. 1993; Payne et al. 1998). The first row contained the friend's attribute weights for the six attributes. The next six rows contained the attribute values for each alternative. At the bottom of the screen, participants could select their preferred alternative among the six available alternatives. At the top of the screen, an indicator showed the decision number. Participants were instructed to take as much time as they wished to view information about weights and attribute values and make decisions. Participants made one practice decision followed by 15 actual decisions. The experimental session took roughly 15 minutes.

## **14.2 Experimental Variables**

### **14.2.1 Visual Separators**

Visual separators were manipulated by adding either no lines, lines separating alternatives, or lines separating attributes in the choice set. Participants were randomly assigned to make decisions using an interface that included no lines, lines between alternatives, or lines between attributes. Other aspects of the interface were identical across conditions.

### **14.2.2 Attribute Correlation**

Following previous research, to provide a strong test of adaptivity (Bettman et al. 1993), attribute correlation was manipulated as a within-subjects factor. Five choice sets were randomly generated with a positive attribute correlation of .60 and five choice sets were randomly generated with a negative attribute correlation of -.20 (Following Bettman et al. 1993, we selected .60 for the positive correlation. Because the extent to which

attribute correlations can be negative is reduced as the number of attributes increases (Bettman et al. 1993), -.20 is the lowest possible correlation obtainable given six attributes). The order of choice sets was random but the same for all participants.

Overall, this study uses a mixed 3 x 2 x 5 repeated measures design. The first factor is the three levels of visual separators (no lines, lines separating alternatives, or lines separating attributes), which is manipulated between-subjects. The next factor is the two levels of interattribute correlation (negative correlation and positive correlation), which is manipulated within-subjects. Repetition, five decision tasks for each correlation level for a total of 10, is also a within-subjects factor.

### 14.3 Dependent Variables

#### 14.3.1 Decision Quality

The quality of decisions was assessed by comparing the weighted additive utility of the chosen alternative with those of the best and worst choice in each choice set (Payne, Bettman, and Johnson 1988). This measure is bounded by 1 if the best choice is selected and 0 if the worse choice is selected.

*Choice Quality*

$$= \frac{\text{Weighted Additive Value}_{\text{Choice}} - \text{Weighted Additive Value}_{\text{Worst}}}{\text{Weighted Additive Value}_{\text{Best}} - \text{Weighted Additive Value}_{\text{Worst}}}$$

### 14.4 Results

Table 6 summarizes the observed mean values of choice quality. The mean quality of participants' choices was fairly high ( $M_{\text{choice quality}} = .81$ ). Throughout the paper, we use repeated-measures analyses to account for within-subjects effects.



**Table 6**  
**Mean Decision Quality<sup>a</sup> in Study 2.2**

Correlation level	Visual separator		
	No lines	Lines between alternatives	Lines between attributes
Negative correlation	.79 (.02)	.86 (.02)	.72 (.02)
Positive correlation	.87 (.01)	.88 (.01)	.84 (.01)

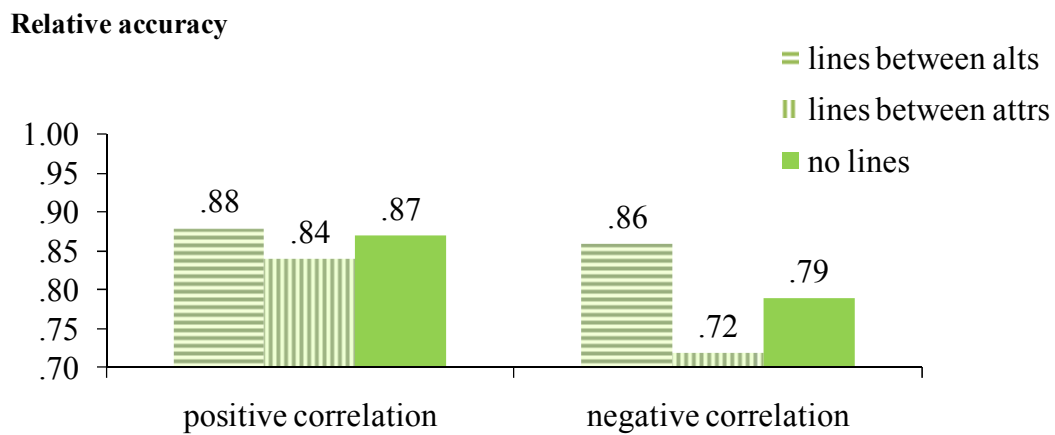
Note: Standard deviations are given in parentheses.

<sup>a</sup>Quality of choice relative to the best and worst alternatives in the choice set.

#### 14.4.1 Decision Quality

In support of Hypothesis 4, visual separators between alternatives will increase choice quality and visual separators between attributes will hurt decision quality to a greater extent when attributes are negatively correlated versus when attributes are positively correlated, a significant interaction between visual separators and correlation on decision quality ( $F(2, 82) = 5.08, p < .01$ ) was found. Planned contrasts show that: 1) When attributes were negatively correlated, adding lines between alternatives increased choice quality compared to adding no lines in the choice set (.86 vs. .79,  $t(82) = 2.28, p < .05$ ) and adding lines between attributes decreased choice quality compared to adding no lines in the choice set (.79 vs. .72,  $t(82) = 2.25, p < .05$ ), and 2) When attributes were positively correlated, adding lines between alternatives did not affect choice quality (.88 vs. .87,  $t(82) < 1$ ) and adding lines between attributes only marginally decreased choice quality (.84 vs. .87,  $t(82) = 1.88, p < .10$ ; see Figure 9).

In addition to the hypothesized interaction, a main effect of visual separators ( $F(2, 82) = 12.65, p < .0001$ ) was found. Planned comparisons show that: 1) choice quality was lower when adding lines between attributes than when adding no lines in the choice set (.78 vs. .83,  $t(54) = 2.83, p < .01$ ), and 2) choice quality was higher when adding lines between alternatives than when adding lines between attributes (.87 vs. .83,  $t(56) = 2.09, p < .0001$ ). Consistent with previous research (Bettman et al. 1993), results show that decision quality was lower when attributes were negatively correlated than when attributes were positively correlated (.79 vs. .86,  $t(82) = 4.87, p < .0001$ ).



**Figure 9**

## **Study 2.2: Visual Design and Decision Quality**

### **14.5 Discussion**

Results from Study 2.2 provide support for the prediction that the effect of visual separators on decision performance depends on the choice context. In particular, our results suggest that the effect of visual separators on decision outcomes depends on

interattribute correlation. When attributes were negatively correlated, adding visual separators between alternatives increased choice quality while adding visual separators between attributes decreased choice quality. When attributes were positively correlated, visual separators had minimal effects on choice quality. This is because the use of different types of decision strategies is more impactful under negatively correlated environments than under positively correlated environments and visual separators can change the use of decision strategies. To understand the processes that visual separators may lead to, Study 2.3 examines the effects of visual separators on decision processes.

## **CHAPTER 15**

### **STUDY 2.3**

By changing the visual characteristics of the information environment, visual separators may change the way in which decisions are made. Process tracing methods such as Mouselab (Payne et al.1988), eye tracking (Russo and Doshier 1983), or verbal protocols (Jarvenpaa 1989), may be used to assess decision processes. In particular, information acquisition patterns can be assessed by examining the extent to which decision makers process by-attribute or by-alternative. Processing by attribute is associated with the use of non-compensatory decision rules, in which decision makers tend to make comparisons on a single attribute; whereas processing by-alternative is more associated with compensatory decision making processes in which tradeoffs are made across multiple attributes. Decision efficiency can be assessed the average amount of time per acquisition and the average searching distance between acquisitions. In addition, the percentage of unique cells examined and proportion of time spent on the most important attribute (Payne et al.1988) were collected to assess the amount of information acquisitions and processing selectivity, although there are no specific hypotheses for these variables.

#### **15.1 Stimuli and Procedure**

In Study 2.3, we manipulated the same variables and followed the same procedure as Study 2.2. In particular, visual separators were manipulated at three levels between subjects (i.e., no lines, lines between alternatives, or lines between attributes) and the intercorrelation among attributes was manipulated at two levels within subjects (i.e.,

negative correlation and positive correlation). As in Study 2.2, participants made one practice and 10 actual decisions from randomly generated choice sets consisting of six alternatives and six attributes and their associated attribute weights. To measure decision processes, Study 2.3 used an information acquisition system similar to Mouselab (Payne et al. 1988) developed specifically for this study (see Figure 10). Prior research has shown that patterns of information acquisitions in Mouselab are similar to those from eyetracking studies (Lohse and Johnson 1996).

Subjects (97 undergraduate students) participated in the study for course credit. Information about attribute weights and values was hidden behind opaque boxes. Information was available for only one box at a time. Moving the mouse cursor over a box revealed its contents, and information remained visible until the cursor was moved out of the box. Participants could open as many boxes as many times as they wished. The acquisition system recorded boxes opened, and the order and time they were opened.

## **15.2 Dependent Variables**

Decision quality was measured as in Study 2.2. In addition, information acquisition pattern (Payne et al. 1988), decision efficiency, amount of information examined, and processing selectivity were collected to assess the ways in which visual separators affect decision processes.

## “No lines” condition

**Practice Decision**

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the coffee makers (1 = worst and 1,000 = best).

	Material	Ease of Use	Durability	Warranty	Settings	Size
Importance						
Coffeemaker B45						
Coffeemaker V24						
Coffeemaker R47						
Coffeemaker Z61						
Coffeemaker F52						
Coffeemaker B32						

Please Choose One: ☐ Coffeemaker B45 ☐ Coffeemaker V24 ☐ Coffeemaker R47 ☐ Coffeemaker Z61 ☐ Coffeemaker F52 ☐ Coffeemaker B32

**Continue**

## “Lines separating alternatives” condition

**Practice Decision**

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the coffee makers (1 = worst and 1,000 = best).

	Material	Ease of Use	Durability	Warranty	Settings	Size
Importance						
Coffeemaker B45						
Coffeemaker V24						
Coffeemaker R47						
Coffeemaker Z61						
Coffeemaker F52						
Coffeemaker B32						

Please Choose One: ☐ Coffeemaker B45 ☐ Coffeemaker V24 ☐ Coffeemaker R47 ☐ Coffeemaker Z61 ☐ Coffeemaker F52 ☐ Coffeemaker B32

**Continue**

## “Lines separating attributes” condition

**Practice Decision**

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the coffee makers (1 = worst and 1,000 = best).

	Material	Ease of Use	Durability	Warranty	Settings	Size
Importance						
Coffeemaker B45						
Coffeemaker V24						
Coffeemaker R47						
Coffeemaker Z61						
Coffeemaker F52						
Coffeemaker B32						

Please Choose One: ☐ Coffeemaker B45 ☐ Coffeemaker V24 ☐ Coffeemaker R47 ☐ Coffeemaker Z61 ☐ Coffeemaker F52 ☐ Coffeemaker B32

**Continue**

Figure 10

## Study 3: Experimental Manipulations

### 15.2.1 Acquisition Pattern

Moving the mouse from one attribute to another attribute for the same alternative was coded as an alternative-based transition. Moving the mouse from one alternative to another for the same attribute was coded as an attribute-based transition (Payne et al. 1988). An acquisition pattern index was calculated by taking the number of alternative-

based transitions minus the number of attribute-based transitions and then dividing by the sum of alternative- and attribute-based transitions (Bettman et al. 1993). This index ranges from -1 (indicating only attribute-based processing) to +1 (indicating only alternative-based processing).

### 15.2.2 Decision Efficiency

To examine the effect of visual separators on decision efficiency, two measures were used: 1) average time per acquisition was measured, which was calculated by taking a ratio between the amount of time spent acquiring information and the number of acquisitions, and 2) information adjacency index ( i.e., average distance between acquisitions), which was measured by taking a ratio between the total searching distance and the number of movements, and then dividing this ratio by the diagonal distance of the matrix (i.e., standardized). This measure is bounded by zero (e.g., acquisition of adjacent information) and one (e.g., one moves the cursor diagonally from one box to another).

$$\text{Information Adjacency Index} = \frac{\sum_{i=1}^n \text{Distance}_{\text{between } i \text{ and } (i+1)}}{\frac{n}{\text{Diagonal Distance}}}$$

Where i is the movement, n is the number of movements, diagonal distance is the diagonal distance of the choice set.

### 15.2.3 Amount of Information Examined

To measure the amount of information examined, the percentage of unique cells examined was calculated by taking a ratio of the number of unique acquisitions and the total number of cells (i.e., 36).

#### 15.2.4 Processing Selectivity

To examine processing selectivity, the proportion of time spent on the most important attribute was calculated by taking a ratio of the time spent acquiring information about the most important attribute and the total acquisition time.

### 15.3 Results

Study 2.3 followed the same analysis as Study 2.2. Means for the dependent measures are presented in Table 7. The overall quality of participants' choices was high ( $M_{\text{choice quality}} = .83$ ). As in previous research (Bettman et al. 1993), we found significant effects of practice and correlation.

#### 15.3.1 Decision Quality

In further support of Hypothesis 4, the effects of visual separators on decision quality are greater when attributes are negatively correlated than when they are positively correlated, there was a significant interaction between visual separators and correlation on decision quality ( $F(2, 94) = 7.24, p < .01$ ). Planned comparisons show that when attributes were negatively correlated, adding lines between alternatives increased choice quality (.86 vs. .80,  $t(94) = 2.38, p < .05$ ) while adding lines between attributes decreased choice quality (.75 vs. .80,  $t(94) = 2.21, p < .05$ ). When attributes were positively correlated, adding lines between attributes marginally decreased choice quality (.87 vs. .89,  $t(94) = 1.91, p < .07$ ); adding lines between alternatives did not have an impact on choice quality (.88 vs. .89,  $t(94) = 1.18, ns$ ). As in Study 2, choice quality was higher when lines separated alternatives rather than attributes in the choice set (.86 vs. .78,  $F(1,$



94) = 13.33,  $p < .0001$ ). Following prior research, decision quality was lower when attributes were negatively correlated than when attributes were positively correlated (Bettman et al. 1993).

**Table 7: The Effect of Visual Separators on Decision-making in Study 2.3**

		Visual separators level		
	Correlation level	No lines	Lines between alternatives	Lines between attributes
Decision Quality	Negative correlation	.80 (.016)	.86 (.018)	.75 (.018)
	Positive correlation	.89 (.008)	.88 (.008)	.87 (.008)
Transition Pattern <sup>b</sup>	Negative correlation	-.009 (.068)	.221 (.050)	-.143 (.053)
	Positive correlation	-.068 (.058)	.196 (.062)	-.277 (.066)
Time per Acquisition <sup>c</sup>	Negative correlation	1.01 (.026)	1.00 (.028)	1.07 (.029)
	Positive correlation	1.06 (.029)	.98 (.031)	1.10 (.032)
Information Adjacency Index <sup>d</sup>	Negative correlation	.22 (.005)	.21 (.005)	.24 (.005)
	Positive correlation	.23 (.006)	.22 (.007)	.21 (.007)
The Percentage of Unique Cells Examined	Negative correlation	40% (.023)	45% (.024)	35% (.025)
	Positive correlation	39% (.023)	42% (.024)	28% (.025)
The Proportion of Time Spent on the Most Important Attribute	Negative correlation	46% (.020)	41% (.022)	54% (.022)
	Positive correlation	49% (.029)	43% (.031)	61% (.032)

<sup>b</sup>Index of the relative amount of attribute (-) vs. alternative-based (+) processing.

<sup>c</sup>A ratio between the amount of time spent acquiring information and the number of acquisitions.

<sup>d</sup>A ratio between the total searching distance and the number of movements divided by the diagonal distance of the choice set.

### 15.3.2 Acquisition Pattern

Among the 97 participants, two did not acquire enough information on at least one of the 10 choice sets to calculate the acquisition pattern. To test the idea that visual separators encourage particular types of decision strategies. I found a main effect of visual separators ( $F(2, 92) = 14.99, p < .0001$ ) on transition pattern and multiple comparisons show that lines between alternatives led to by-alternative processing (.21 vs. -.04,  $t(65) = 3.40, p < .01$ ) while lines between attributes led to by-attribute processing (-.21 vs. -.04,  $t(62) = 2.31, p < .05$ ).

In support of Hypothesis 2, that visual separators reduce adaptivity to the choice context, I found an interaction effect between visual separators and attribute correlation on transition pattern ( $F(2, 92) = 2.01, p < .07$ , one-tailed). In particular, planned comparisons show that the difference in information processing patterns under negative and positive correlation was smaller when there were visual separators between alternatives (.221 vs. .196,  $t(92) < 1$ , ns) than that in the no lines condition (-.004 vs. -.076,  $t(92) = 1.69, p < .05$ , one-tailed). However, contrary to Hypothesis 2, we found that the difference in information acquisition patterns under negative and positive correlation with lines between attributes (-.143 vs. -.277,  $t(92) = 3.35, p < .01$ ) was greater than that in the no lines condition (-.004 vs. -.076,  $t(92) = 1.69, p < .05$ , one-tailed). Therefore, partial support was found for Hypothesis 2 (see Figure 11).

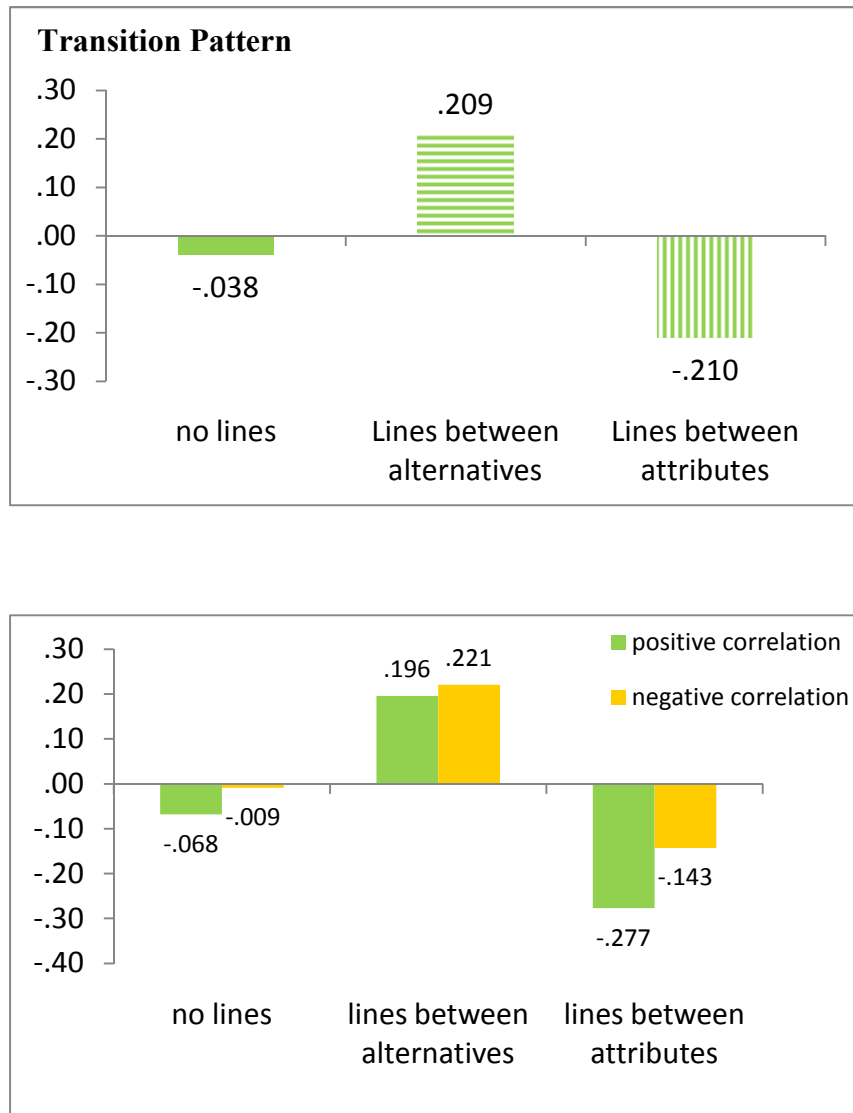
### 15.3.3 Decision Efficiency

Hypothesis 3 proposed that when attributes are negatively correlated, visual separators between alternatives increase decision efficiency while those between attributes decrease decision efficiency; under positive correlation, visual separators

always increase decision efficiency. To test this hypothesis, we first examined the effect of visual separators on average time per acquisition. Among the 97 participants, one did not acquire any information on at least one of the 10 choice sets to calculate the average time per acquisition. An interaction between correlation and visual separators on the average time per acquisition was found ( $F(2, 93) = 4.19, p < .05$ ). As predicted, planned comparison results show that when attributes were negatively correlated, relative to the no lines condition, lines between attributes increased average time per acquisition (1.01 vs. 1.07,  $t(93) = 1.62, p < .05$ , one-tailed); when attributes were positively correlated, relative to the no lines condition, lines between alternatives decreased average time per acquisition (1.06 vs. .98,  $t(93) = 2.05, p < .05$ ). Other effects were not significant.

Second, we assessed the effects of visual separators on decision efficiency through the information adjacency index (i.e., average distance between acquisitions). Results show an interaction between visual separators and attribute correlation on information adjacency ( $F(2, 94) = 9.81, p < .0001$ ). Planned comparisons show that when attributes were negatively correlated, compared to the no lines condition, lines between alternatives decreased average distance between acquisitions (.221 vs. .209,  $t(94) = 1.86, p < .05$ , one-tailed) while line between attributes increased it (.221 vs. .238,  $t(94) = 2.43, p < .05$ ). However, when attributes were positively correlated, compared to the no lines conditions, both lines between alternatives (.229 vs. .215,  $t(94) = 1.56, p < .06$ , one-tailed) and those between attributes (.229 vs. .209,  $t(94) = 2.22, p < .05$ ) decreased average distance between acquisitions. Thus, we found support for Hypothesis 3 according to the information adjacency index but only partial support according to

average time per acquisition. In addition, results show a main effect of visual separators on average distance between acquisitions ( $F(2, 94) = 2.38, p < .10$ ).



**Figure 11**

### **Study 2.3: Visual Design and Information Acquisition Pattern**

#### 15.3.4 Amount of Information Examined

Results for the percentage of unique cells examined are reported for completeness. GLM results show an interaction between visual separators and attribute correlation on the percentage of unique cells examined ( $F(2, 94) = 3.59, p < .05$ ). Planned comparisons show that under negative correlation, visual separators between alternatives increased the percentage of unique cells examined (46% vs. 40%,  $t(94) = 1.70, p < .05$ , one-tailed) and visual separators between attributes decreased the percentage of unique cells examined (35% vs. 40%,  $t(94) = 1.67, p < .06$ , one-tailed). However, under positive correlation, visual separators between alternatives did not have an effect on the percentage of unique cells examined (42% vs. 39%,  $t(94) < 1$ ) while visual separators between attributes decreased the percentage of unique cells examined (28% vs. 39%,  $t(94) = 3.30, p < .01$ ). In addition, results show a main effect of visual separators on the percentage of unique cells examined ( $F(2, 94) = 7.27, p < .01$ ).

#### 15.3.5 Processing Selectivity

Results for the proportion of time spent on the most important attribute are reported for completeness. We did not detect an interaction effect on this variable. Results show a main effect of visual separators on the percentage of time spent on the most important attribute ( $F(2, 94) = 9.34, p < .0001$ ). Multiple comparisons show that relative to the no lines condition, lines between alternatives decreased the percentage of time spent on the most important attribute (42% vs. 48%,  $t(65) = 1.68, p < .05$ , one-tailed) and lines between attributes increased the percentage of time spent on the most important attribute (57% vs. 48%,  $t(64) = 2.76, p < .01$ ). These results further support the idea that visual separators between alternatives encourage compensatory decision

processes while those between attributes encourage non-compensatory decision processes.

#### **15.4 Discussion**

Results from Study 2.3 provide additional insights into the effects of visual separators on decision making. As in Study 2.2, when attributes were negatively correlated, consumers made better decisions when visual separators separated choice alternatives but made worse decisions when visual separators separated product attributes, however, these differences were reduced when product attributes were positively correlated. Further, process tracing results suggest that visual separators encourage particular types of information processing such that lines between product alternatives led to compensatory decision processes such as a more by-alternative processing and a lower processing selectivity, whereas lines between product attributes led to non-compensatory decision processes such as a more by-attribute processing and a greater processing selectivity. Partial support was found for the proposal that visual separators reduce consumers' adaptivity to characteristics of underlying environments. For example, compared to no visual separators in a choice set, visual separators between choice alternatives reduced differences in information acquisition patterns in negatively and positively correlated environments, suggesting that visual separators restrict consumers' use of different decision strategies in different choice contexts. These processing results also help explain results for decision quality in Study 2.2. Because visual separators between choice alternatives encourage compensatory decision processes and increase decision efficiency as well as information acquisitions, while those between

attributes discourage compensatory decision processes, decrease decision efficiency as well as information acquisitions, under negative correlation, visual separators between alternatives improved decision quality while those between attributes decreased decision quality. In addition, results suggest that although visual separators do not improve decision quality when attributes are positively correlated, they can help increase decision-making efficiency. For example, our results show that both visual separators between alternatives and these between attributes decreased average distance between acquisitions when attributes were positively correlated. However, according to average time per acquisition, we only found partial support for the decision efficiency argument such that when attributes were positively correlated, lines between alternatives decreased average time per acquisition but no effect found for lines between attributes; when attributes were negatively correlated, lines between attributes increased average time per acquisition but no effect found for lines between alternatives.

Study 2.3 shows that certain types of visual separators can help increase decision efficiency and amount of information acquired, especially when product attributes are negatively correlated, where trade-offs among product attributes are needed to make a good decision. Because consumers are often unable to make trade-offs among product attributes (Pieters and Warlop 1999) due to insufficient time and high cognitive load under time pressure, visual separators should have more of an impact on decision quality in negative correlated environments. Study 2.4 is designed to explore the effect of visual separators on decision making under time pressure.

## **CHAPTER 16**

### **STUDY 2.4: THE EFFECTS OF VISUAL SEPARATORS ON DECISION MAKING UNDER TIME PRESSURE**

Prior research has shown that time pressure is an important variable to consider in the domain of consumer decision making because a normative decision strategy such as weighted additive decision strategy may be more cognitive demanding and less attractive under time pressure (Simon 1981; Payne et al. 1988; Tabatabaei 2002). Due to high cognitive load and insufficient time, under time pressure, decision makers are unable to make trade-offs between pros and cons across all available information and may choose to accelerate information processing, filter part of the available information, and/or shift their information processing strategies (Pieters and Warlop 1999; Janiszewski 1998; Payne et al. 1988). In addition, today's consumers face large amounts of information and online decision aids, such as visual separators can help consumers deal with increasing amounts of information.

Study 2.3 shows that visual separators improve decision efficiency by guiding consumers' decision processes and making the acquisition of information more systematic. In particular, without time constraints, visual separators between alternatives increase the amount of information examined, decrease average time spent per acquisition, and increase search efficiency. Under time pressure, more systematic and efficient processing of information should help consumers make better choices; particularly in complex information environments that require tradeoffs among attributes. For example, when product attributes are negatively correlated, more systematic and



efficient processing of information should allow consumers to better assess tradeoffs among attributes. However, when attributes are positively correlated, and decision makers do not need to make tradeoffs among attributes, the advantages of more systematic processing will be less apparent. In other words, under time pressure, visual separators separating alternatives can help more in negatively correlated environments. In addition, although prior studies show that without time constraints, visual separators separating attributes may decrease decision efficiency in negatively correlated environments, there is a reason to believe that relative to no visual separators in the information environments, under time pressure, visual separators separating attributes can make navigation easier by guiding consumers' decision processes—they should be able to help decision makers acquire more information in a relatively systematic way (rather than randomly scan the information). Thus, under time pressure, both visual separators between alternative and those between attributes should have a greater impact on decision quality in negatively correlated environments than in positively correlated environments in which people can make good decisions by using heuristics (Bettman et al. 1993).

In addition to improving decision quality under time pressure, visual separators should also reduce selectivity in information processing. Prior research shows that decision makers tend to process information selectively under time pressure by focusing on acquiring a subset of information or the most important attribute (Payne et al. 1993; Tabatabaei 2002). Because visual separators increase decision efficiency, this should enable decision makers to consider more information and be less selective. Together, these arguments suggest that:

- H5:** Under time pressure, visual separators will increase decision quality to a greater extent when attributes are negatively correlated than when attributes are positively correlated.
- H6:** Under time pressure, visual separators will: a) increase decision efficiency, b) increase the amount of information examined, and c) decrease processing selectivity.

### **16.1 Stimuli and Procedure**

In Study 2.4, we manipulated the same variables and followed the same process tracing experimental procedure as Study 2.3, except that participants were given only 45 seconds for each choice. Following prior research (Lurie 2004; Payne et al. 1988), at the top of the screen, a timer showed the time remaining for a particular decision and after 45 seconds, moving the mouse over the boxes no longer revealed the information about attribute weights and attribute values, and a message appeared asking participants to “please make a choice.”; see Figure 12). Subjects (97 undergraduate students) participated in the study for course credit.

### **16.2 Dependent Variables**

Dependent variables in Study 2.4 were measured as in Study 2.3.

## “No lines” condition

Decision # 1

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the coffee makers (1 = worst and 1,000 = best).

	Importance	Material	Ease of Use	Durability	Warranty	Settings	Size
Coffeemaker H32	504						
Coffeemaker V42							
Coffeemaker Z44							
Coffeemaker X86							
Coffeemaker T64							
Coffeemaker I65							

Please Choose One: ☐ Coffeemaker H32 ☐ Coffeemaker V42 ☐ Coffeemaker Z44 ☐ Coffeemaker X86 ☐ Coffeemaker T64 ☐ Coffeemaker I65

Question 1: How satisfied are you with the coffee maker you chose for your brand?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Satisfied

Question 2: How hard was it to make this decision?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not hard Very hard

Question 3: How confident are you that you made the right choice?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Confident

Continue

## “Lines separating alternatives” condition

Decision # 1

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the coffee makers (1 = worst and 1,000 = best).

	Importance	Material	Ease of Use	Durability	Warranty	Settings	Size
Coffeemaker H32	504						
Coffeemaker V42							
Coffeemaker Z44							
Coffeemaker X86							
Coffeemaker T64							
Coffeemaker I65							

Please Choose One: ☐ Coffeemaker H32 ☐ Coffeemaker V42 ☐ Coffeemaker Z44 ☐ Coffeemaker X86 ☐ Coffeemaker T64 ☐ Coffeemaker I65

Question 1: How satisfied are you with the coffee maker you chose for your brand?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Satisfied

Question 2: How hard was it to make this decision?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not hard Very hard

Question 3: How confident are you that you made the right choice?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Confident

Continue

## “Lines separating attributes” condition

Decision # 1

The top row lists the importance weights from 1 to 100. Remember to use these weights in your decisions. The other rows list the values of each attribute for each of the coffee makers (1 = worst and 1,000 = best).

	Importance	Material	Ease of Use	Durability	Warranty	Settings	Size
Coffeemaker H32	504						
Coffeemaker V42							
Coffeemaker Z44							
Coffeemaker X86							
Coffeemaker T64							
Coffeemaker I65							

Please Choose One: ☐ Coffeemaker H32 ☐ Coffeemaker V42 ☐ Coffeemaker Z44 ☐ Coffeemaker X86 ☐ Coffeemaker T64 ☐ Coffeemaker I65

Question 1: How satisfied are you with the coffee maker you chose for your brand?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Satisfied

Question 2: How hard was it to make this decision?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not hard Very hard

Question 3: How confident are you that you made the right choice?  
☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7  
 Not at all Very Confident

Continue

Figure 12

## Study 2.4: Experimental Manipulations

### 16.3 Results

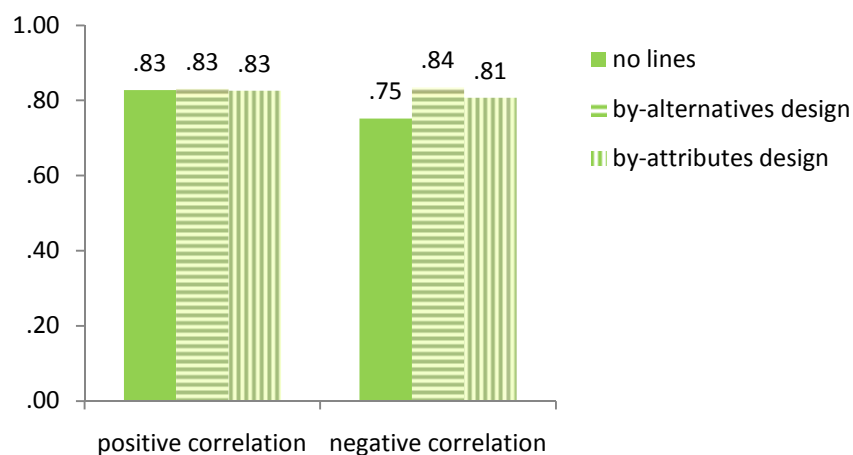
Study 2.4 followed the same analysis as Study 2.3. Means for the dependent measures are presented in Table 8.

**Table 8****Study 2.4: Effects of Visual Separators on Decision-making under Time Pressure**

	Correlation level	Visual separators level		
		No lines	Lines between alternatives	Lines between attributes
Decision Quality	Negative correlation	.75 (.019)	.84 (.020)	.81 (.019)
	Positive correlation	.83 (.014)	.83 (.015)	.83 (.014)
Transition Pattern	Negative correlation	-.162 (.068)	.050 (.069)	-.184 (.067)
	Positive correlation	-.227 (.079)	.084 (.081)	-.195 (.078)
Time per Acquisition	Negative correlation	1.19 (.051)	1.17 (.053)	1.31 (.051)
	Positive correlation	1.25 (.056)	1.19 (.058)	1.33 (.056)
Information Adjacency Index	Negative correlation	.24 (.006)	.19 (.006)	.20 (.006)
	Positive correlation	.23 (.004)	.19 (.004)	.20 (.004)
The Percentage of Unique Cells Examined	Negative correlation	28% (.019)	35% (.020)	33% (.019)
	Positive correlation	26% (.020)	32% (.021)	30% (.020)
The Proportion of Time Spent on the Most Important Attribute	Negative correlation	58% (.027)	48% (.028)	49% (.027)
	Positive correlation	63% (.034)	50% (.035)	53% (.034)

### 16.3.1 Decision Quality

In support of Hypothesis 5, that under time pressure, visual separators increase decision quality to a greater extent when attributes are negatively correlated than when they are positively correlated, there was a significant interaction between visual separators and correlation on decision quality ( $F(2, 94) = 3.19, p < .05$ ). Multiple comparisons show that when attributes were negatively correlated, adding lines between alternatives (.84 vs. .75,  $t(94) = 2.96, p < .01$ ) and adding lines between attributes (.81 vs. .75,  $t(94) = 2.04, p < .05$ ) increased choice quality. When attributes were positively correlated, however, no such significant results were found (*ns*) (see Figure 13). We also found the main effect of visual separators ( $F(2, 94) = 2.93, p < .05$ , one-tailed) on choice quality such that adding lines between alternatives (.83 vs. .79,  $t(62) = 2.40, p < .05$ ) as well as adding lines between attributes into the choice set (.82 vs. .79,  $t(62) = 1.48, p < .08$ , one-tailed) improved choice quality. Following prior research, decision quality was lower when attributes were negatively correlated than when attributes were positively correlated (Bettman et al. 1993)



**Figure 13**  
**Study 2.4: Visual Design and Decision Quality under Time Pressure**

### 16.3.2 Decision Efficiency

Hypothesis 6a proposes that under time pressure, visual separators increase decision efficiency. GLM results failed to show a significant main effect of visual separators on average time per acquisition (*ns*) and we did not find support for Hypothesis 6a in terms of this efficiency measure. However, we did find support for this hypothesis in terms of information adjacency index. In support of Hypothesis 6a, results show a significant main effect of visual separators ( $F(2, 94) = 35.97, p < .0001$ ) on average searching distance per movement. Multiple comparison results show that compared to no lines in the choice set, both lines between alternatives (.23 vs. .19,  $t(62) = 8.33, p < .0001$ ) and lines between attributes (.23 vs. .20,  $t(62) = 6.67, p < .0001$ ) decreased average searching distance per movement. Other effects were not significant. Overall, we found partial support for Hypothesis 6a.

### 16.3.3 Amount of Information Examined

In support of Hypothesis 6b, that under time pressure, visual separators increase the amount of information examined, GLM results show a main effect of visual separators ( $F(2, 94) = 3.37, p < .05$ ) on the percentage of unique cells examined. Multiple comparisons show that both lines separating alternatives (34% vs. 27%,  $t(62) = 2.55, p < .05$ ) and lines separating attributes (31% vs. 27%,  $t(62) = 1.68, p < .05$ , one-tailed) increased the percentage of unique cells examined. Following the prior research, we also found that the percentage of unique cells examined was higher when attributes were negatively correlated than when they were positively correlated (32% vs. 29%,  $F(1, 94) = 18.81, p < .0001$ ). Other effects were not significant.

#### 16.3.4 Processing Selectivity

We also found support for Hypothesis 6c, that under time pressure, visual separators decrease processing selectivity. Results show a main effect of visual separators on the proportion of time spent on the most important attribute ( $F(2, 94) = 4.24, p < .05$ ). Multiple comparisons show that both lines between alternatives (49% vs. 60%,  $t(62) = 2.67, p < .01$ ) and lines between attributes (51% vs. 60%,  $t(62) = 2.33, p < .05$ ) decreased the proportion of time spent on the most important attribute. Following prior research, the proportion of time spent on the most important attribute was lower when attributes were negative than when they were positive (51% vs. 55%,  $F(1, 94) = 10.75, p < .01$ ; Bettman et al. 1993). Other effects were not significant.

#### 16.3.5 Acquisition Pattern

Although there are no specific hypotheses for acquisition pattern, results for this variable are reported for completeness. Among the 97 participants, one did not acquire enough information on at least one of the 10 choice sets to calculate the acquisition pattern. GLM results show a significant main effect of visual separators on acquisition pattern ( $F(2, 93) = 4.37, p < .05$ ). Multiple comparisons show that under time pressure, adding lines between alternatives into the choice set led to a more by-alternative processing (.067 vs. -.195,  $t(61) = 2.59, p < .05$ ). Adding lines between attributes into the choice set did not make a difference on the acquisition pattern under time pressure (-.189 vs. -.195,  $t(62) < 1, ns$ ). This may in part be because under time pressure, non-compensatory decision strategies are more likely to be used—relative to no visual separators, visual separators between alternatives shift the use of decision strategy but visual separators between attributes don't.

## **16.4 Discussion**

Study 2.4 suggests that under time pressure, both visual separators separating alternatives and those separating attributes help consumers make a better decision, especially when attributes are negatively correlated. These results are different than those without time pressure in which visual separators between alternatives improve choice quality but those between attributes hurt choice quality. Under time pressure, both types of visual separators increase decision efficiency—decreasing average searching distance between acquisitions, increasing the amount of information examined, and decreasing processing selectivity, such as proportion of time spent on the most important attribute. Results for decision quality show that these efficiency improvements are especially helpful when attributes are negatively correlated.



## **CHAPTER 17**

### **GENERAL DISCUSSION**

#### **17.1 Summary and theoretical implications**

Web designers use visual separators in decision environments to increase the aesthetic appeal of their websites and make navigation easier. However, our results suggest that these visual separators may systematically affect consumer preferences, decision processes, and decision outcomes. Although our illustrative analysis of top retailing websites suggests little consensus on which types of visual separators are best, our results show that they may reverse consumers' preferences in evaluating the same set of products, lead consumers to make a worse decision in some choice environments, and shift information processing behaviors.

Study 2.1 tests the idea that visual separators lead to preference reversals. Results from Study 2.1 show that visual separators between alternatives lead people to pay more for the product superior on the easy-to-evaluate attribute while visual separators between attributes lead people to pay more for the product superior on the hard-to-evaluate attribute. In other words, visual separators can lead to separate or joint evaluations (Hsee 1996) when products are presented jointly. Importantly, these preference-reversal results occur even when product options, product attributes, evaluation scales (e.g., choice vs. matching; Tversky, Sattath, and Slovic 1988), or evaluation modes (e.g., joint evaluation vs. separate evaluation; Hsee 1996) are held constant.

Study 2.2 examines the hypothesis that visual separators and choice context interact to affect decision outcomes. In support of this hypothesis, results show that when product attributes are negatively correlated, visually separating alternatives improves

decision quality but visually separating attributes hurts decision quality. However, visual separators do not affect decision quality when attributes are positively correlated.

Study 2.3 replicates the results of visual separators on choice quality and extends to examine that the effect of visual separators on decision processes. Process tracing results suggest that visual separators between choice alternatives or attributes encourage particular types of information processing and, more interestingly, reduce adaptivity to choice contexts. In particular, visual separators between choice alternatives reduced the difference in information acquisition pattern between negatively correlated environments and positively correlated environments. This suggests that visual separators reduce the extent to which consumers change their decision strategies in different choice contexts. In addition, results from Study 2.3 suggest that although visual separators do not improve decision quality when attributes were positively correlated, they help increase decision-making efficiency in such environments. For example, visual separators between alternatives decreased average time per acquisition when attributes were positively correlated.

Finally, Study 2.4 examines the impact of visual separators on decision making under time pressure. Results suggest that, under time pressure, both visual separators separating alternatives and visual separators separating attributes help consumers make a better decision, particularly when attributes are negatively correlated. In addition, process tracing results show that both types of visual separators increase decision efficiency by decreasing average searching distance per movement, increasing the amount of information examined, and decreasing processing selectivity—such as the proportion of time spent on the most important attribute. This is because visual separators guide

consumers' decision processes and decrease the uses of acceleration, filtering, or heuristics under time pressure, compared to no visual separators. Because visual separators enable decision makers to consider more factors, they are more impactful when attributes are negatively correlated where trade-offs are needed to make a good decision.

From a theoretical standpoint, these results are interesting because without changing evaluation scales or evaluation modes, visual separators can reverse consumer preferences. It also appears that consumers do not always make better decisions when visual separators are present. Rather, the effect of visual separators depends on the characteristics of the decision environments. More generally, this research offers new ways to think about consumers' adaptivity. First, we suggest that keeping other things constant, visual separators can systematically affect consumer choices. Second, while visual separators encourage particular types of information processing, such as by-alternative and by-attribute processing, they discourage adaptivity to the choice context. Therefore, the impact of visual separators on decision outcomes depends on the fit between decision processes (encouraged by specific types of visual separators) and the choice context.

## **17.2 Managerial implications**

Beyond such theoretical implications, this research suggests that in addition to the initial display of product information, strategic placement of visual separators is likely to affect consumer decision making. For example, our results show that visual separators lead to preference reversal—lines between alternatives lead to a preference for the

product with greater easy-to-evaluate attribute value and lines between attributes lead to a preference for the product with greater hard-to-evaluate attribute value. Thus, when displaying choice alternatives having the easy-to-evaluate attribute and the hard-to-evaluate attribute, managers need to consider which types of visual separators to use. For example, if the manager wants to promote a digital camera model with a lighter weight (i.e., easy-to-evaluate attribute) but less exposure modes (i.e., hard-to-evaluate attribute), she may need to display cameras with visual separators separating choice alternatives (rather than camera attributes).

Further, while visual separators between attributes will hurt choice quality in negatively correlated environments, visual separators between alternatives will improve choice quality in such environments. Even though such visual separators in the choice set may not affect decision performance in positively correlated environments, they help increase decision efficiency, allowing consumers to make decisions in a relatively shorter period of time. These suggest that in displaying product alternatives, marketers should consider the types of visual separators, between alternatives or between attributes, as well as the contextual characteristics of the environments such as whether product attributes are positively correlated or negatively correlated. While for consumers to make decisions under time constraints, both displaying visual separators between choice alternatives and between product attributes can help them make a better decision.

### **17.3 Limitations and future research**

It is important to point out two of the limitations of this work. First, the convenience samples used are not representative of the U.S. population as a whole.

Second, for experimental control, these studies were limited to a particular visual separators manipulation and lacked much of the richness of real websites. Future research could seek to address these issues, perhaps examining other types of visual separators on commercial websites. For example, how different colors of bars or different shapes of lines in the choice set might affect decision making.

Future research could also study the extent to which visual separators guide versus restrict consumer behavior. For example, reactance theory (Brehm and Brehm 1981) proposes that any obstacle makes it harder for a decision maker to choose a choice alternative that he or she expects to have the freedom to choose will constitute a threat to his/her freedom. As a result, the decision maker may choose the initially nonpreferred alternative in order to eliminate such as threat. It would be interesting to test the effect of visual separators on decision-making when people have high versus low psychological reactance. According to psychological reactance theory, it would be also interesting to test whether different types of visual separators, for instance, wider bars (vs. narrower bars), may reverse the initial decision strategies visual separators lead to (i.e., wider separators between alternatives lead to non-compensatory decision processes while those between attributes lead to compensatory decision processes).

## APPENDIX A

### COMPARING MULTIPLE- AND SINGLE-TOOL CHOICE STRATEGIES

To help us better understand the results of study 1.5, particularly, to explain the results that sorting improves decision quality when elimination is present but hurts when elimination is absent under negatively correlated environments, but always helps regardless of the availability of eliminations in positively correlated environments, we compared a multiple-tool choice strategy (i.e., sorting and elimination) to a single-tool choice strategy (i.e., sorting only) to 10 choice sets in study 1.5. Given that participants in study 1.5 sorted more than once on average ( $M = 2.85$ ), usually sorted first then eliminated ( $M_{\text{time difference}} = 2.96$  seconds), generally eliminated about 4 alternatives ( $M = 3.50$ ), and sorted more when elimination was available than when elimination was not available (3.96 versus 1.70;  $F(1, 57) = 13.21, p < .01$ ), the following multiple tool strategy was created: Sort on the most important attribute, eliminate the lowest 4 alternatives on that sorted attribute, sort again on the second most important attribute, and choose the top listed alternative in the choice set. This strategy was compared to a sort-only strategy in which alternatives are sorted on the most important attribute and the top-listed alternative is chosen.

Applying the sort and elimination strategy to the 5 negative correlation choice sets and 5 positive correlation choice sets shows that 3 out of 5 choices were the best alternatives in both cases. However, applying the sort only strategy to the 5 negative correlation choice sets and 5 positive correlation choice sets reduces these probabilities to 1 out of 5 and 3 out of 5, respectively. These results show that, in negatively correlated environments, when both sorting and elimination tools are available, the probability that

the best alternative is listed at the top of a choice set is 60% versus 20% when only sorting is available. However, under positively correlated environments, the probability that the best alternative is listed first is 60% regardless of whether elimination is available. The intuition for this result is that eliminating low quality alternatives on an attribute after an initial sort means that subsequent sorting on other attributes increases the probability that the best alternative is listed on the top of a choice set under negative correlation. On the other hand, sorting without elimination when attributes are negatively correlated means that poor alternatives are much more likely to be listed first.

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